Journal of Environmental Management 370 (2024) 122705

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Research article

Predicting daily firefighting personnel deployment trends in the western United States

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ARTICLE INFO

Keywords:
CatBoost
Wildfires
Firefighters
Modeling
Firefighting personnel
Machine learning

ABSTRACT

Projected increases in wildfire frequency, size, and severity may further stress already scarce firefighting resources in the western United States that are in high demand. Machine learning is a promising field with the ability to model firefighting resource usage without compromising dataset size or complexity. In this study, the Categorical Boosting (CatBoost) model was used with historical (2012–2020) wildfire data to train three models that calculate predicted daily counts of 1) total assigned personnel (total personnel), 2) assigned personnel that are at the fire (ground personnel), and 3) assigned personnel that either work with aircraft or in management (air/overhead personnel) based on daily wildfire characteristics. The main drivers behind personnel assignment under current management practices included structures threatened, acres burned, point of fire origin, and fire priority. While contextual variables such as preparedness level and the presence of other large fires were among the least important, the importance of fire priority reveals that factors beyond the features of the fire itself are influential in personnel assignment. CatBoost model predictions provide an historical context to firefighting resource assignment and could also be used to inform decision-makers and managers about future issues facing firefighting resources in the western United States given projected changes in climate.

1. Introduction

Wildfire activity is projected to increase in the conterminous United States due to increasing annual temperatures, changing precipitation patterns, and seasonal weather changes brought about by anthropogenic climate change (Gao et al., 2021; Huang et al., 2015). These increasing wildfire frequencies are exacerbated in the western conterminous United States, where a combination of anthropogenic climate change, fuel buildup due to fire exclusion practices, and human development have resulted in further increases in fire frequency as well as increases in fire size and severity that are expected to continue into the foreseeable future (Abatzoglou and Williams, 2016; Barbero et al., 2015; Calkin et al., 2015; Dye et al., 2024; Higuera and Abatzoglou, 2021; Riley and Loehman, 2016; Riley et al., 2019; Williams, 2013). In 2020 alone, over 2.5 million hectares were burned in the western United States (Higuera and Abatzoglou, 2021). Furthermore, the United States is experiencing a rapid increase in the development of wildland-urban interfaces (WUI) where human life and properties are more susceptible to wildfires (Bayham and Yoder, 2020; Radeloff et al., 2018) and may demand extra attention from firefighting managers. Present and future threats from changing wildfire seasonality, frequencies, sizes, and severities, are expected to increase demand for firefighting resources (i.e., personnel and equipment) (Abatzoglou et al., 2021; Bloem et al., 2022; Cullen et al., 2021; McGinnis et al., 2023).

In the US, wildland firefighting resources are provided by many agencies, including federal, state, county, and city employees. Wildfire response across these agencies is organized into three levels: local, regional, and national. At the local level, personnel stationed in the area provide initial response capabilities on their agencies' land as well as land governed by agencies with which they have mutual aid agreements. There are over 250 local dispatching centers that manage this local-level response. When wildland fires exceed initial response capacity, these fires are managed as large fires by incident management teams, with personnel generally coming from across the region or country to help provide capacity. The US is split into ten geographic coordination areas (also known as Geographic Area Coordination Centers (GACCs)), and management at this level moves personnel around the regions to supplement local areas experiencing elevated levels of fire activity (see

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https://doi.org/10.1016/j.jenvman.2024.122705
Received 5 June 2024; Received in revised form 23 September 2024; Accepted 27 September 2024

Fig. 1 for a map of seven of the ten GACCs). The National Interagency Coordination Center facilitates resource allocations between geographic areas experiencing elevated fire activity. This three-level system is governed by the concept of "total mobility" of all firefighting suppression resources, which requires that personnel and equipment will respond to wildland fires in the areas of greatest need (National Interagency Fire Center Multi-Agency Coordinating Group, 2024).

An increase in demand for firefighting resources due to climate change would likely exacerbate existing issues involving limited firefighting resources. The costs of firefighting are already challenging agencies with fire suppression responsibilities. For example, in 1995, 15% of the budget of the United States Forest Service (USFS) was devoted to wildfire suppression. In 2018, almost 66% of the USFS budget ($2.6 billion) was devoted to wildfire suppression (National Interagency Fire Center, 2024; U.S. Forest Service, 2015), and the costs are expected to continue to rise (Prestemon et al., 2022). Firefighting resources become scarce during times of simultaneous severe fires, a severity which is projected to increase (Abatzoglou et al., 2021; Flannigan et al., 2013; Wasserman and Mueller, 2023), with most fire seasons characterized by unfilled requests for suppression resources (Belval et al., 2020; Hand et al., 2017; Stonesifer et al., 2017). Previous research has found that Type 1 crews (firefighters with the highest qualifications and experience, see Interagency Standards for Fire and Fire Aviation Operations Group (2024) for more information) in particular show high levels of usage across seasons (2014–2018), meaning that many crews spend substantial time in the field (Belval et al., 2018, 2020; Stonesifer et al., 2017). Additional use of these resources has been associated with additional risk of accumulated fatigue and potential detrimental impacts on crew members (Belval et al., 2018; Cuenca-Lozano and Ramirez-Garcia, 2023; Smith et al., 2018). Quantifying the increasing pressure on limited firefighting resources and personnel motivates the creation of a model that can be used for planning purposes.

Studies using empirical models and simulations to analyze firefighting suppression costs and assignments have used expert knowledge to mathematically define explicit relationships between resource usage/cost and environmental and human factors to determine which factors have the largest impact on firefighting decisions. Such studies on the dollar value of suppression costs tended to use parametric regressions, with findings often including the positive correlations between suppression costs and fire weather, extreme fire behavior, and the value of threatened structures (Gebert et al., 2007; Hand et al., 2016; Liang et al., 2008). Other studies focused on resource assignments beyond the dollar value. Hand et al. (2017) used wildfire characteristics and assigned incident management teams along with a utility-theoretic model to perform linear regression on productive capacity from all resources used to demonstrate how resource use may vary substantially across incident management teams in the United States. Bayham et al. (2020) used a two-step regression model to determine how expected weather and evacuations affect ordered resources in the western United States. Bayham and Yoder (2020) created an econometric model that focused on minimizing wildfire damage to determine what factors, such as weather conditions, location, and proximity to buildings, were the most influential on resource assignment in the western United States and found that fires that threatened homes (especially high-cost homes) tended to receive more resource allocation. Cullen et al. (2024) used an Ordinary Least Squares (OLS) approach to predict the number of total personnel days (excluding personnel working with aircraft) and peak personnel count based on fire ignition conditions for the years 2017–2020 in the western US. Wells et al. (2024) used a generalized linear mixed model (GLMM) to model the number of ground personnel used per incident per fire day with a further goal of using these models to determine how ground personnel use changed due to COVID while controlling for all other variables.

These studies on resource assignment generally found that the number/value of houses threatened by fire and expectations of increasing fire weather/behavior were the driving forces behind resource assignment. Resource assignment may also be further affected by institutional factors such as the Incident Management Team assigned

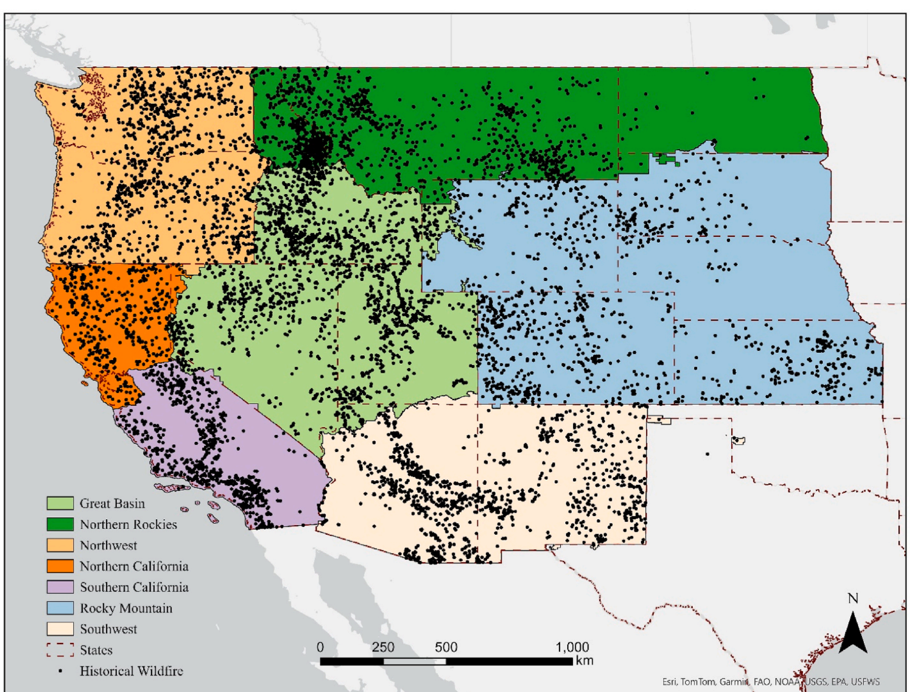

Fig. 1. Study area and fires of focus. Western Geographic Area Coordination Centers (GACCs) and origins of fires (2012–2020) considered from the US National Incident Management System Incident Status Summary (ICS-209-PLUS), the National Incident Management Situation Report (IMSR), and the Resource Ordering and Status System (ROSS)/Interagency Resources Ordering Capability (IROC) datasets across the western United States. Some fires shown here are not in the ROSS/IROC dataset.

and the GACC region in which the fire took place. Most of these studies had some amount of unexplained variance in their final models, which points to noisy, nonlinear wildfire systems or the influence of factors not included in the models. Hand et al. (2016), for example, presented a model predicting suppression expenditure in the western United States for the years 2006–2011 that was unable to explain about 40% of the variance in expenditure. Bayham et al. (2020) predicted more specific resource usages within the western United States for the years 2007–2013 and created models that predicted type 1 crew and type 2 crew (crew "type" denotes what the crew is qualified to do; see Interagency Standards for Fire and Fire Aviation Operations Group (2024) for more information) usage that were unable to explain between about 50 and 70% of the variance in the data. Models used in two recent studies that directly predicted daily personnel counts, similar to our investigation, were only able to explain less than 45% of the variability in data not yet seen by the models (Cullen et al., 2024; Wells et al., 2024).

Limitations exist in these studies. For example, the relationship between the independent variables and resource assignment are assumed to be linear or log-linear. The usage of generalized linear regression models in these studies might not capture nonlinear relationships present in datasets with large numbers of variables that have complex relationships with each other as well as the predicted variable. Datasets used may be relatively small in sampling size (e.g., only covering a couple hundred fires or less) (Bayham and Yoder, 2020; Hand et al., 2016, 2017; Liang et al., 2008). Studies used the entire datasets for their models as well (i.e., not out-of-sample testing of predicted ability), which provides no information on the generalizability of the models to new data and potentially results in overfit models (a situation where a model only does well on observed data and does poorly on unobserved data). Only two very recent studies directly predicted personnel counts, highlighting a scarcity of research in this area and emphasizing a need for further studies (Cullen et al., 2024; Wells et al., 2024).

To develop models that accurately predict daily resource needs while specifically considering nonlinear relationships, other methods such as machine learning should be considered. Machine learning is a field of computer science that focuses on using algorithms to develop a model that can generate more accurate predictions than traditional methods (de la Riva et al., 2004; Jain et al., 2020; Shmuel and Heifetz, 2023a, 2023b). Machine learning algorithms require fewer assumptions than traditional methods and do not require researchers to directly create parametric relationships for the model, making them well-suited when compared to statistical methods using linear assumptions for data characterized by complex, not fully understood nonlinear patterns or trends present within the field of wildfire modelling (Jain et al., 2020; Pérez-Porras et al., 2021; Shmuel and Heifetz, 2023b). Generally, machine learning can handle larger datasets in less time and with less computational cost, especially when compared to physics-based methods (Jain et al., 2020; Shi et al., 2023; Shmuel and Heifetz, 2023a). Machine learning has already demonstrated promising results in personnel assignment prediction. Costafreda-Aumedes et al. (2016) used information from a historical wildfire database in combination with an artificial neural network (ANN) to create a model that could predict assigned personnel and vehicle counts for large fires (defined as above 100 ha in this study) in Spain. However, the predictions in this study were not calculated at a daily temporal resolution but instead on a fire-by-fire basis. This study was performed in Spain, and no similar study has been performed in the United States yet.

One specific kind of machine learning model is an offshoot of the Gradient Boosting Model (GBM) known as the Categorical Boosting (CatBoost) model. Like the GBM, CatBoost sequentially creates weak decision trees based on sequentially reweighed and resampled datasets and the minimization of a loss function. The advantage of the GBM process is that it works well on data that is noisy and nonlinear (Hancock and Khoshgoftaar, 2020; Huang et al., 2019; Prokhorenkova et al., 2018). CatBoost further differentiates itself from the GBM via ordered boosting, creating oblivious decision trees, handling categorical variables via ordered target statistics, and combining categorical variables in some splits. These extra functions help to reduce bias, prevent target leakage, and work against overfitting (Huang et al., 2019; Prokhorenkova et al., 2018). CatBoost models have been used in the study of wildfires. Abujayyab et al. (2022) predicted wildfire susceptibility in forests in Turkey with five different kinds of boosting models and found that the CatBoost model achieved the highest testing accuracy of 95.47%. Kang et al. (2020) calculated an hourly forest fire risk index for forests across South Korea using both a CatBoost model and obtained an area under curve (AUC) of 0.8434. The advantages of the CatBoost model and the relevant usage of CatBoost in wildfire research make the model a prime candidate for predicting daily firefighting personnel counts.

Our goal is to gauge the effectiveness of CatBoost models on predicting the daily assignment of firefighting personnel within the western United States based on historical wildfire data using CatBoost models. Very few previous studies have focused on daily predictions in firefighting personnel assignment, a gap we seek to fill. We intend for these models to be used in highlighting the general trend of firefighting personnel assignment under current management practices and not to be used for predicting specific fires. We further use these model to understand which drivers are the most influential on daily assigned personnel counts with a focus on the nonlinear relationships present.

2. Study area and methods

2.1. Western conterminous United States

The study area for this project is the western conterminous United States (Fig. 1). Specifically, we used the boundaries of the western GACCs (any GACC that is not the Eastern Area Coordination Center, Southern Area Coordination Center, or Alaska Interagency Coordination Center). GACCs are defined by fire managers for the purposes of resource assignment and management (National Interagency Fire Center, 2019).

2.2. Fire data (2012–2020)

2.2.1. ICS-209-PLUS

The ICS-209-PLUS dataset is a simplified collection of situation reports (sitreps) from the US National Incident Management System Incident Situation (ICS-209) reports (St. Denis et al., 2023). The dataset includes a table comprised of ICS-209 sitreps, which are filed daily to weekly on wildfire incidents and describe specific characteristics associated with the fire of interest, with fires each receiving separate sitreps. An ICS-209 sitrep is usually created for a wildfire if the fire exceeds 100 acres in timber vegetation or 300 acres in grass/brush, although smaller fires may still be included if the fire is believed to be significant (St. Denis et al., 2023). We excluded sitreps that described firefighting efforts in response to pre-planned/prescribed fires. We further removed sitreps that contained obvious errors (records with unrealistic total personnel counts in the hundreds of thousands, number of threatened structures that were in the hundreds of thousands, or locations not in the conterminous United States). Missing values in the threatened structures field can safely be assumed to equate to no structures threatened and filled with zeros. Negative wildfire fire spread rates, which are impossible and only occurred on the first sitreps of some fires, were replaced with the current acreage reported by that sitrep.

We created a new variable called "structures in fire" (STR_INFIRE) by taking the sum of the number of structures damaged by the fire and the number of structures destroyed by the fire. The structures-in-fire variable was created to simplify the data with the consideration that results from wildfire simulators may be used as input for our models and will not be able to distinguish between damaged and destroyed buildings.

2.2.2. National incident management situation report (IMSR)

The IMSR dataset, a fire dataset from the National Interagency

Coordination Center about GACCs, provides information about preparedness levels and uncontained large fires (meaning the large fire does not have a secured perimeter) at the national and regional scales as well as fire priority at a regional scale (Nguyen et al., 2024). These data reflect the availability of and demands on firefighting resources and the foci of management. At a preparedness level of 1, resources are more available, while at the maximum preparedness level of 5, most resources are already assigned to fires. This dataset also includes the number of uncontained large fires burning in the US each day. A higher number of uncontained large fires causes a higher level of competition for firefighting resources. Fire priority is also captured in this dataset, and it reflects which fires were the highest priority for the GACCs, with higher numbers corresponding to lower priority fires. Including fire priority in the model may help capture some of the institutional and situational factors influencing personnel assignment.

2.2.3. Resource ordering and status system (ROSS) and the interagency resources ordering capability (IROC)

ROSS and IROC are systems used by dispatchers to manage requests for firefighting resources. These software applications track and archive information on the requests they receive and fill, including information about fire characteristics, response personnel and equipment characteristics, and assignment details (Belval et al., 2020). ROSS was used prior to March 2020, after which ROSS was replaced by IROC. Data elements from these systems are archived and can be combined into a single record of assignments. For conciseness, we will refer to this data combination as "ROSS" hereafter. From these data, we were able to obtain the number of ground personnel and the number of air/overhead personnel assigned to each fire. Ground personnel were defined as personnel on the ground at the fire; this includes hand crews and engine crews. Air personnel were defined as personnel operating aircraft and assisting in aircraft operations. Overhead personnel were defined as all personnel in charge of managing resources for the fire. Air and overhead personnel counts were combined due to the difficulty of separating out the two personnel counts. Aviation personnel are sometimes ordered separately from their equipment, which can result in the aviation personnel being ordered under a code that classifies them as overhead personnel (please see Lockheed Martin Enterprise Solutions & Services (ES&S) Ross Project Office (2012) and National Dispatch Efficiency Working Group (2024) for more information on the ROSS dataset structure).

2.3. Data manipulation and cleanup

Sitreps from the ICS-209-PLUS dataset were assigned a GACC based on the initially reported fire coordinates. We then joined the ICS-209-PLUS to the national and regional IMSR reports according to both the GACC region and report date. Sitreps that did not occur on the same date as a national IMSR report or regional IMSR report within the same GACC were assigned the values of the previous report if that report was within 14 days. Otherwise, values of one were assigned for national or regional preparedness levels and values of zero were assigned for national or regional uncontained large fires. Fire priority from the IMSR wildfire reports was joined based on fire name and report date. If no matching report was found, then a value of -1 was assigned for fire priority. Several IMSR reports on fire priority with the same exact date matched the same sitrep in three different fires. Considering that in every case these fire priorities reported disagreed and it was impossible in some situations to tell which reported fire priority came first, we assigned a value of -1 for these sitreps as well.

After joining the datasets, we filtered the joined dataset such that for each fire, if multiple sitreps were created on the same day, only the sitrep with the highest reported total personnel count was kept. The removal of the other sitreps helped to prevent overemphasis on fires that had more reports written within the same time frame as other fires. We then removed sitreps that likely covered the "mop-up" phase of the fire when personnel are primarily monitoring the fire after containment has been achieved. We discarded these sitreps due to these actions being beyond the scope of our project. For each fire, sitrep removal occurred if two consecutive days of zero personnel counts occurred and if all of the subsequent sitreps had personnel values of less than 20, in which case only the first sitrep with a zero personnel count was kept. A value of 20 was chosen due to any personnel count below that number likely being a mop-up crew (Belval et al., 2022). We further cleaned the dataset by only keeping fires that started in the western region of the United States, which included any fire that did not occur in the Eastern Area Coordination Center, Southern Area Coordination Center, or the Alaska Interagency Coordination Center. A small subset of sitreps contained percent contained/completed values that detailed a maximum management area instead of a percentage: these sitreps were dropped. Finally, situation reports that had missing values in any of our variables of choice (Table 1) were dropped from the data. These data were dropped to prevent the arbitrary selection of some value that may not reflect reality and also since doing so still retained an acceptable number of sitreps. The resulting dataset contained 44,981 sitreps for 6,443 fires (Fig. 1) and was used in the model focused on total personnel counts.

From the previous dataset, we created a new dataset by joining the ROSS data based on fire ID. If no matches were present in the ROSS dataset, then the data for that fire were discarded. Personnel on the ground and air/overhead personnel were separately summed from the ROSS data and joined along with assigned agency (Forest Service, Department of Interior, or other). The resulting dataset contained 37,680 sitreps and 4,837 fires. Note that personnel counts in this dataset and the previous one include personnel from any type of crew, not just the type 1 and type 2 crews discussed in previous studies.

The datasets before the ROSS join and after were separately randomly split by fire into 5 different groups such that all sitreps belonging to one fire were all assigned to the same group. These groups were used to maintain consistent 5-fold cross-validation across model tests. All sitreps belonging to one fire were kept within the same group to prevent information leakage within the CatBoost models.

2.4. CatBoost models

2.4.1. Process of the CatBoost model

The CatBoost model works like the General Boosting Model (GBM) by sequentially producing weak decision trees (Hancock and Khoshgoftaar, 2020; Huang et al., 2019). Trees are trained on a bootstrap of the training data and designed to minimize the sample residuals that are calculated based on a loss function. Samples with the worst predictions are weighed more heavily, while weights are reduced for more correctly predicted samples. The next decision tree is created based on a bootstrap of the reweighed training data (Hancock and Khoshgoftaar, 2020; Huang et al., 2019). In this way, each subsequent decision tree focuses on the data with the most unexplained variance from the prior tree. After the user-defined number of trees is produced, the final output is formed from the summation of the outputs of all of the decision trees weighed by a user-defined learning rate (Hancock and Khoshgoftaar, 2020; Huang et al., 2019).

CatBoost differs from the GBM through its handling of categorical variables, its usage of ordered boosting, and its development of oblivious decision trees (Huang et al., 2019; Prokhorenkova et al., 2018). For each categorical variable, CatBoost performs two different processes. For categorical variables with less than a user-defined number of different categorical values, one-hot encoding is performed. For the rest of the categorical values that go over the number, ordered target statistics are calculated. Ordered target statistics is a process in which the order of the categorical values and their associated output values are shuffled, and each categorical value is replaced with a new value based on how many times the same categorical value has been seen before in the shuffle and some user-defined statistic performed with the output values of the previous identical categorical values (Huang et al., 2019;

Table 1
Input predictor variables.

Predictor Variable	Description	Data Type	Data Source
ACRES	Acres burned to date	Numeric	ICS-209-PLUS
DISCOVERY_DOY	Day of year when the wildfire was discovered	Numeric	ICS-209-PLUS
FUEL_MODEL	Fuel Model of area based on the Anderson Fire Behavior Fuel Model (Anderson, 1982)	Categorical	ICS-209-PLUS
PCT_CONTAINED_ COMPLETED	Percentage of fire that is contained or completed	Numeric/ Percentage	ICS-209-PLUS
POO_LATITUDE	Starting latitude of fire	Numeric	ICS-209-PLUS
POO_LONGITUDE	Starting longitude of fire	Numeric	ICS-209-PLUS
STR_INFIRE	Structures inside the fire	Numeric	ICS-209-PLUS
STR_THREATENED	Structures currently threatened by fire	Numeric	ICS-209-PLUS
WF_FSR	Wildfire Fire Spread Rate (acres burned since last report over days since last report)	Numeric	ICS-209-PLUS
AGENCY	Fire agency assigned to fire	Categorical	ROSS
NATIONAL_UNCONTAINED_LARGE_FIRE	Number of concurrent uncontained large fires across the US	Numeric	IMSR
REGIONAL_ UNCONTAINED_LARGE_FIRE	Number of concurrent uncontained large fires within GACC	Numeric	IMSR
NATIONAL_ PREPAREDNESS _LEVEL	Measure of firefighting availability across the US	Categorical	IMSR
REGIONAL_ PREPAREDNESS_LEVEL	Measure of firefighting availability within GACC	Categorical	IMSR
FirePriority	Ordinal measure of firefighting priority	Ordinal	IMSR

Prokhorenkova et al., 2018). Furthermore, when using these variables to produce splits in trees, CatBoost may combine different categorical variables together to enable better predictions via the reduction of bias (Huang et al., 2019; Prokhorenkova et al., 2018). When performing the ordered boosting, CatBoost creates several random permutations (ordered lists) on the input training data. For each of these ordered lists except one withheld list, a separate model is built to predict each observation such that the model is trained on all observations before the target observation in the permutation and updated based on the model targeting the next observation in line. These models are used to design the splits in the trees, while the one withheld ordered list is used to decide leaf values. Ordered boosting helps to reduce overfitting (Huang et al., 2019; Prokhorenkova et al., 2018). Decision trees in the final model are oblivious, which means that every split in the same layer is identical. Oblivious trees have the benefit of being balanced, reducing processing time, and counteracting overfitting (Huang et al., 2019; Prokhorenkova et al., 2018).

2.4.2. Model design

We used the CatBoost regressor model from the CatBoost 1.2.2 python library (Prokhorenkova et al., 2018) to create the CatBoost models. Three different CatBoost models were created for three different dependent variables of focus: total personnel count from the ICS-209-PLUS data without the joined ROSS data, ground personnel count from the dataset made after the ROSS data was joined, and air/overhead personnel count from the dataset made after the ROSS data was joined. After testing variables for each model, we decided upon using 14 predictor variables for the model predicting total personnel and included assigned agency for the other models, resulting in 15 variables for the two models predicting ground personnel or air/overhead personnel (Table 1). Predictor variables were selected from the larger set of potential variables based on: (1) compatibility with the machine learning model; (2) data coverage (i.e., not missing in at least 80% of the data), (3) predicting power, and (4) availability (i.e., if the model was to be used for a future scenario, could that variable be obtained through simulation or projection). Despite previous research suggesting expected weather is important (Bayham and Yoder, 2020), expected weather was not included in this model. While weather datasets (both current and projected) are readily available and one could theoretically use the weather on the days after a sitrep to simulate expected weather, that data does not capture what weather was actually forecasted to the firefighters working on the fire, which is much more difficult to determine or project and may differ from what weather would occur.

Point of origin latitude and longitude refers to the coordinates of the ignition point for the fire and remain the same throughout the sitreps for a fire. Structures threatened is not based on any specific metric and is instead decided by the person writing the sitrep. The exact definition of what structures may be threatened varies based on the sitrep author (St. Denis et al., 2023). Percent contained/completed refers to what percentage of the perimeter of the fire has been stopped.

2.4.3. Hyperparameter tuning

After deciding upon the predictor and dependent variables, we performed hyperparameter tuning using the RandomizedSearchCV functions from the scikit-learn 1.4.1 python library (Pedregosa et al., 2011). Hyperparameters refers to the settings of the model that impact model performance but are independent of the input data. RandomizedSearchCV with 5-fold cross-validation using a GroupKFold splitter (splitting on fire ID) was used to test random combinations of hyperparameters for each model (Table 2), with 50,000 combinations for the total model, 60,000 combinations for the ground model, and 57,000 combinations for the air/overhead model. The number of combinations tested for each model differs due to time constraints. Testing tens of thousands of combinations can take several days for each model, even with parallel processing distributed among dozens of cores. Tests were designed to iterate through 10,000 combinations at a time such that code could be run and the results could be examined to decide if testing should continue based on whether improvement in R^2 was occurring on a daily basis. The best combination was chosen based on which resulted in the highest R^2 and produced reasonable results upon observation of the Partial Dependence Plots (i.e., reasonable fluctuations in partial

Table 2
Hyperparameter testing lists.

Hyperparameter	RandomSearchCV Test Lists	GridSearchCV Test Lists
Iterations	[250, 500, 1000–10000 by 1000s]	–
Learning Rate	[0.001, 0.005, 0.01, 0.02, 0.03,0.04–0.2 by 0.02s]	–
Depth	[6,7,8,9,10,11]	–
L2 Leaf Regularization	[2, 4, 6, 7, 8, 9, 10, 25, 50, 75, 100]	–
Random Strength	[1, 2, 4, 8, 10, 20, 30, 40, 50]	–
Random Subspace Method	[0.5, 0.6, 0.7, 0.8, 0.9, 1]	–
Minimum Data in Leaf	[1, 10, 50, 100, 250, 500, 1000]	–
Minimum Variance Sampling (MVS) Regularization	[0, 5, 10, 20, 50, 100, 1000]	–
Boosting Type	–	[Plain, Ordered]
Sampling Frequency	–	[PerTreeLevel, PerTree]

dependence resulting from the data and not unnatural patterns introduced by the model; Partial Dependence Plots are explained shortly). All runs were further performed with a random state of 7 to enable comparisons between runs (by making all random elements in each model the same) and a one hot max size of 0 to make use of CatBoost's ordered target statistics for our categorical variables.

After the RandomizedSearchCV was performed, we took the best results and used them in the GridSearchCV functions from the scikit-learn 1.4.1 python library (Pedregosa et al., 2011). GridSearchCV was set up exactly the same as the previous RandomizedSearchCV, except instead of testing random hyperparameters, we tested four different combinations involving either having plain or ordered boosting and having per tree sampling or per tree level sampling (Table 2). These hyperparameters were tested in this way due to both having only two choices available and due to the potential of these hyperparameters to dramatically increase calculation times if included in the RandomizedSearchCV. The best hyperparameter combinations are listed in Table 3. All hyperparameters that would impact model performance and are not mentioned within this paper were left at default values.

2.5. Assessing and interpreting model results

Each model was assessed with a 5-fold cross-validation using the previously mentioned defined groups as well as the best hyperparameters combinations we could test. The performances of the three fitted models were evaluated by computing the averages of the following metrics from the scikit-learn and SPOTPY libraries: R^2, mean absolute error (MAE), root mean squared error (RMSE), and index of agreement (Houska et al., 2015; Pedregosa et al., 2011).

The influence of each predictor variable was determined by calculating the average normalized importance of each variable across the 5-fold cross-validation for each model. Importance is defined as the difference between the loss value of the model with and without the variable of study (Prokhorenkova et al., 2018). We also examined predictor variable influence by creating Partial Dependence Plots (PDPs) for several variables. PDPs are created by taking 500 random samples, varying the values of one or two predictor variables while keeping the rest constant, and seeing how on average the value of the response variable changes (known as partial dependence). We would like to note that PDPs are created using the data training and testing split from the fifth fold of 5-fold cross-validation for that model.

Table 3
Hyperparameter testing best results.

Hyperparameter	Total	Ground	Air
Iterations	1000	4000	4000
Learning Rate	0.03	0.02	0.02
Depth	10	8	8
L2 Leaf Regularization	2	25	25
Random Strength	10	10	10
Random Subspace Method	0.8	0.6	0.6
Minimum Data in Leaf	1	250	250
MVS Regularization	20	0	0
Boosting Type	Ordered	Ordered	Plain
Sampling Frequency	PerTreeLevel	PerTreeLevel	PerTree

3. Results

3.1. Model predictions and metrics

The R^2 and index of agreement values for the personnel models varied from 0.5020 to 0.6273 and 0.8194 to 0.8759, respectively. The ground personnel model had the highest R^2 and index of agreement values while the total personnel model had the lowest. Mean absolute error (MAE) and root mean square error (RMSE) also varied among the models (Table 4).

All three models share the same issue where extreme values tend to be underestimated (Fig. S1). Furthermore, the predictions tend to differ more from actual higher values than actual lower values, with all three models showing greater ranges in underestimation than overestimation.

As the predicted values increase, the spread of the residuals increases as well (Fig. S2). While the range of residuals corresponding to overestimation and underestimation are about the same in the air/overhead personnel models, underestimation reaches higher extremes than overestimation in the total and ground personnel models.

3.2. Variable importance

Most of the predictors of higher importance relate to physical features of the fire, such as acres burned, location, percent containment/completion, and structures in the fire or threatened by the fire. We found that the most important variable for the total personnel model was longitude (LONGITUDE/long), with an importance of 0.1518. The most important variable for the ground model was structures threatened (STR_THREATENED/threat), with an importance of 0.1493. The most important variable for the air/overhead personnel model was acres (ACRES/acres), with an importance of 0.1819 (Fig. 2). Many of the contextual predictors, such as national/regional uncontained large fires and national/regional preparedness level, were less important. The main exception to this pattern was fire priority (FirePriority), which was found to be the second most important variable in the total personnel model, the sixth most important variable in the ground model, and the fourth most important variable in the air/overhead model.

3.3. Partial dependence plots

We include here the PDPs for what we consider to be the five most important variables across all three models, which include structures threatened, acres burned, longitude and latitude of point of fire origin, and fire priority. Each PDP was created from the last fold of each 5-fold cross-validation.

Structures threatened had a similar influence on the partial dependence of personnel assigned in all three models (Fig. 3) besides a sudden rise and fall between 100 and 350 structures threatened for the total

Table 4
Summary of model metrics.

Model	R^2	MAE	RMSE	Index of Agreement
Total	0.5020	84.63	173.8	0.8194
Ground	0.6273	108.0	206.1	0.8759
Air/Overhead	0.6141	39.21	59.34	0.8647

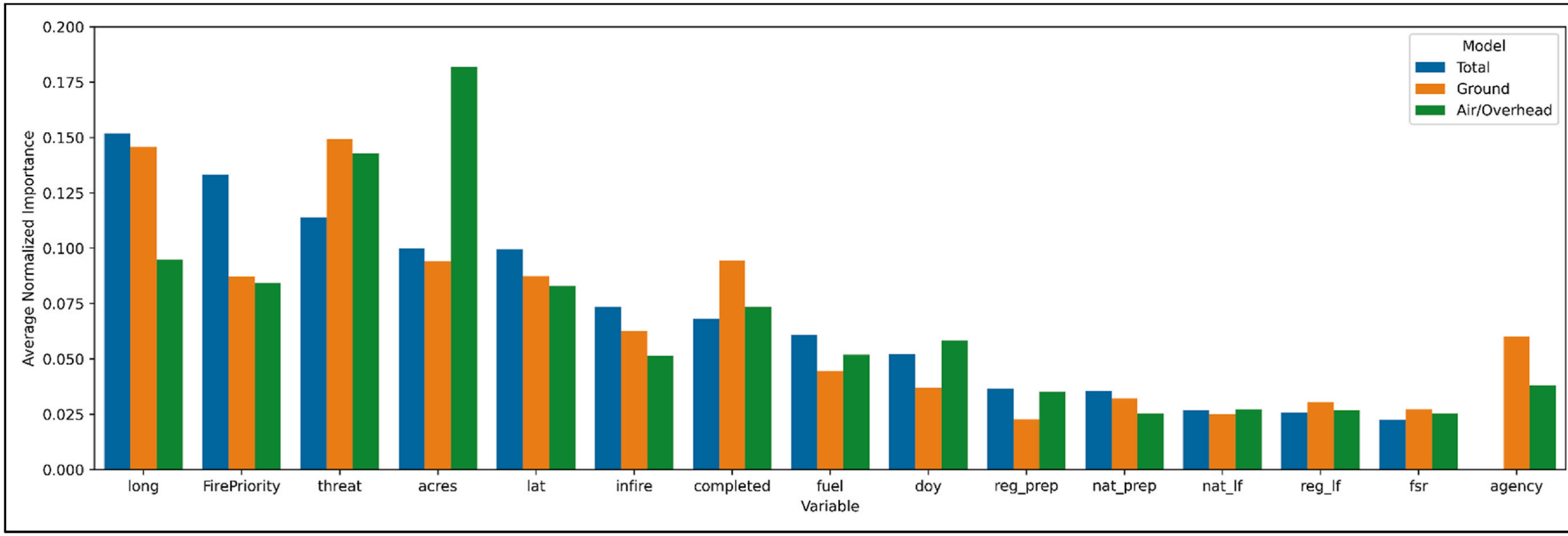

Fig. 2. Average normalized importance plot. Plot of variable importance, ordered with the variable with the highest importance in the total model on the left and the lowest on the right. For each variable, importance in the total personnel, ground personnel, and air/overhead personnel models are plotted. Long refers to the point of origin longitude, FirePriority refers to the fire priority, threat refers to the structures threatened, acres refers to the acres burned, lat refers to the point of origin latitude, infire refers to the structures in fire, completed refers to the percent contained or completed, fuel refers to the fuel model of the area, doy refers to the discovery day of year, nat_prep and reg_prep refer to the national preparedness level and the regional preparedness level, respectively, nat_lf and reg_lf refer to the national uncontained large fires and the regional uncontained large fires, respectively, fsr refers to the wildfire fire spread rate, and agency refers to the agency assigned. Agency was not used in the total personnel model. Fuel, fsr, nat_prep, agency, and reg_prep correspond to categorical predictors and are the total sum of the importance of each type in each category.

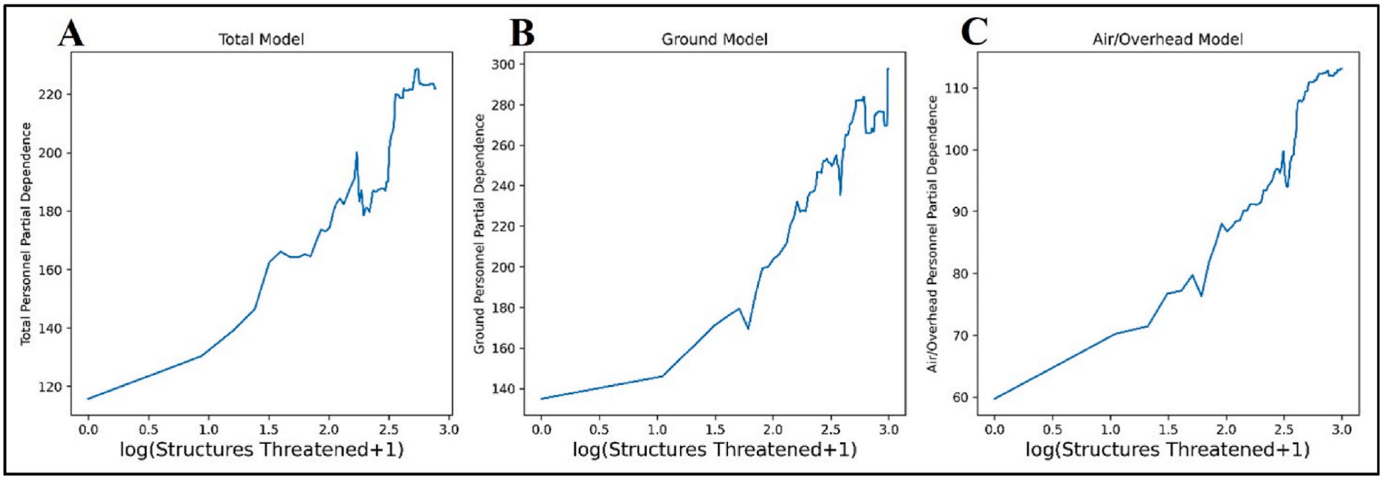

Fig. 3. Structures threatened partial dependence plots. Partial dependence plots for structures threatened for the total model (3A), ground model (3B), and air/overhead model (3C). The x-axis is log-scaled.

model (Fig. 3A) Overall, the number of personnel assigned increases as the number of structures threatened increases, with the same increase in structures threatened resulting in a smaller increase in personnel assigned at higher values of structures threatened. The relationship between the log of structures threatened and personnel assigned is also nonlinear, with tenfold increases in structures threatened having a much larger impact at higher values than lower values.

The influence of acres burned on personnel assignment is similar for all three models (Fig. 4). Overall, as the number of acres burned increases, the number of personnel assigned increases as well, with diminishing returns for the same increase in acres as acres becomes larger. Furthermore, the relationship between the log of acres burned and the partial dependence is somewhat nonlinear, with tenfold increases in acres burned having more impact at higher values than lower values.

Overlaying the partial dependence of personnel assigned on both longitude and latitude on a map of the GACCs of the western United States (Fig. 5) demonstrates that personnel assignments are greatest at more western longitudes, with a trend of decrease in personnel assigned as one goes from west to east across all latitudes. Personnel assignments also tended to be greater at more southern latitudes, although this pattern holds more strongly in western longitudes than eastern latitudes. The highest personnel counts were seen within the two California GACCs (the Northern California GACC and the Southern California GACC).

Lastly, personnel assignment is the highest at priority 1 for fire priority (Fig. 6). In all three models, personnel assignment sharply decreases from priority 1 to about priority 10, after which decreases become more shallow. Around priority 20–30, there is very little change in personnel assigned. Furthermore, the number of personnel assigned to fires with no priority (priority −1) is similar to those assigned to fires with priority between 10 and 15 (not inclusive).

4. Discussion

4.1. Model metrics and predictions

Predicting firefighting resource usage using wildfire data is challenging. Hand et al. (2016) presented a model predicting suppression expenditure in the western United States for the years 2006–2011 with an adjusted R^2 of 0.613, meaning almost 40% of the variance in expenditure was unexplained. Bayham et al. (2020) predicted more specific resource usages within the western United States for the years 2007–2013 and created models that predicted type 1 crew and type 2 crew usage with R^2 values of 0.5019 and 0.3285, respectively. Cullen et al. (2024) and Wells et al. (2024), two studies that more directly modeled assigned personnel, were able to explain 26% and 43.2% of the variability in personnel assignment in data not yet seen by the models, respectively.

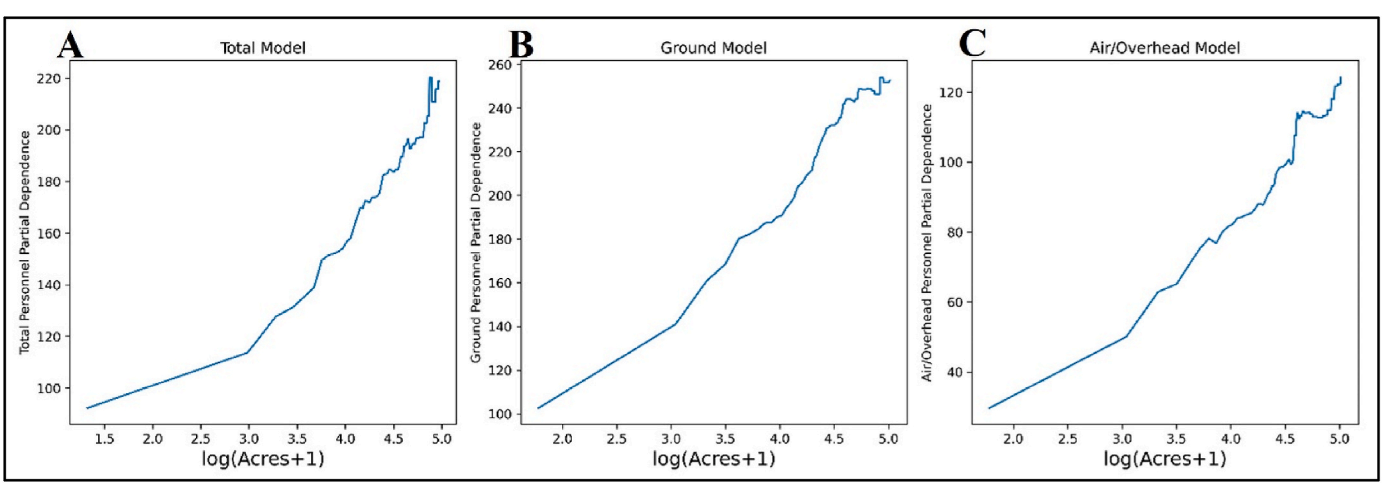

Fig. 4. Acres burned partial dependence plots. Partial dependence plots for acres burned for the total model (4A), ground model (4B), and air/overhead model (4C). The x-axis is log-scaled.

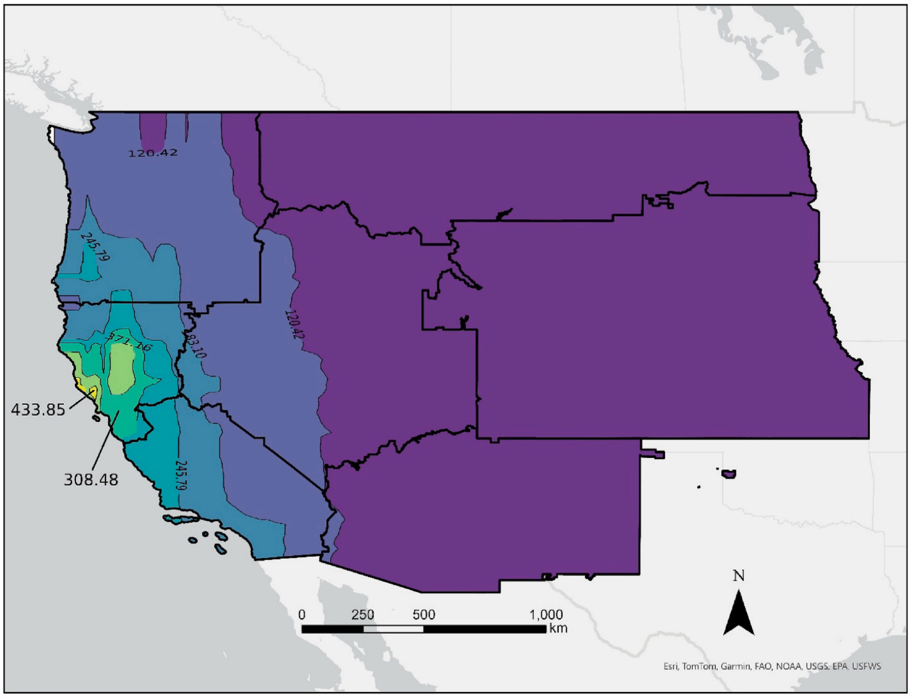

Fig. 5. Two-dimensional point of origin partial dependence plot for the total model. Two-dimensional partial dependence plot of longitude and latitude overlaid on the Geographic Area Coordination Center (GACC) borders of the western United States. Numbers on the borders between colors denote the separating number for those two colors. Numbers with an insert line denote the minimum partial dependence of the color being pointed at. Yellow colors correspond to higher partial dependencies and purple colors correspond to lower partial dependencies. The minimum partial dependence is 77.675 and the maximum partial dependence is 476.59.

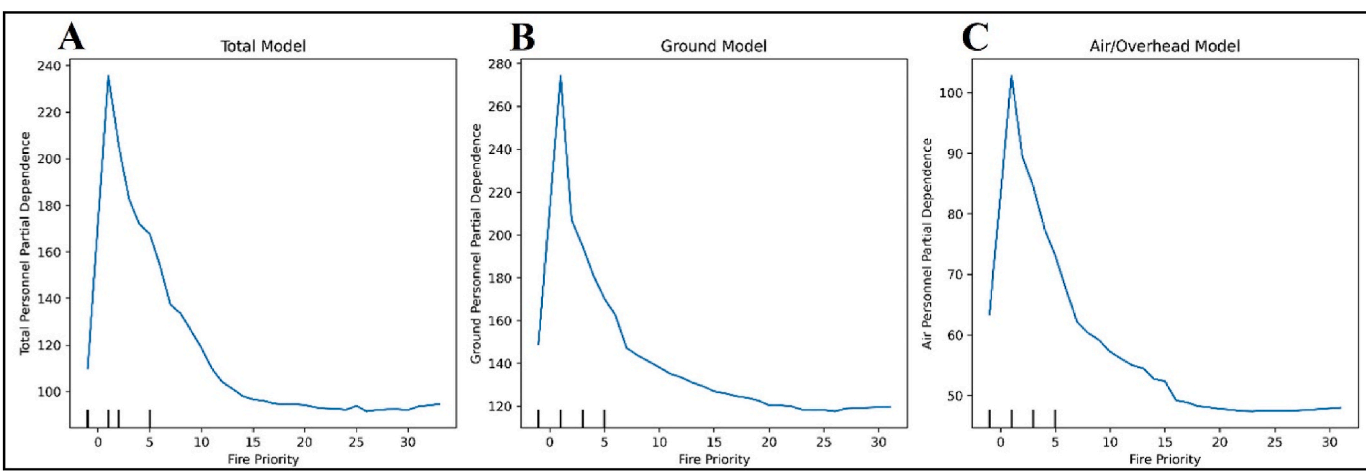

Fig. 6. Fire priority partial dependence plots. Partial dependence plots for fire priority for the total model (6A), ground model (6B), and air/overhead model (6C). Black lines on the x-axis (some of which are overlapping) represent every tenth percentile for fire priority.

All three of our models were able to explain over half of the variability within firefighting personnel assignment (Table 4). The R^2 values calculated for our models are comparable or better than the ones reported by Hand et al. (2016), Bayham et al. (2020), Cullen et al. (2024), and Wells et al. (2024), although we would like to emphasize that our study and the first two of the four studies mentioned here focused on different, albeit similar, variables. Variability not explained in our models is likely due to the stochasticity of the wildfire system combined with inconsistencies in fire reports due to fires being reported by different people at different times and regularity. Sources of variability may also include discrepancies between fire ignition date and fire detection date (especially in remote areas), political or situational factors not included in the model such as incident commander and value of threatened homes, and forecasted weather at the time of the sitrep.

Our models have a more extreme range of underprediction than overprediction. Furthermore, larger predicted values tended to be associated with larger ranges in residuals. Overall, however, our predictions do follow the trend in actual values, and as the observed value increases, the predictions tend to increase proportionally as well. The models all perform as desired given the challenges of the input datasets and capture the general trend of personnel assignment as opposed to predicting specific fires with extreme accuracy.

4.2. Drivers of firefighter personnel assignment

Based on the average normalized importances of the input variables

(Fig. 2), structures threatened and acres burned are both important variables as expected. Structures threatened was the most important variable for the ground personnel model and was in the top three variables for the other two models as well. The influence of structures threatened agrees with results found in previous empirical modeling of firefighter resource costs and usage (Bayham and Yoder, 2020) and, combined with the PDPs (Fig. 3), further shows how firefighter managers focus on the fires with the most potential damage. Acres was found to be the most important variable for the air personnel model and was in the top four variables for the other two models as well. Considering that large fires take up most of firefighting resources (St. Denis et al., 2023), the higher importance of acres is expected as well. However, the relationship between acres and personnel assignment is nonlinear (Fig. 4), and above a certain point increases in fire size do not have a major impact on assigned personnel. At this point, it seems these fires reach a threshold of danger such that additional resource demand cannot be supported, or additional resources may not be needed due to a high capacity already on the fire. Even with log-scaling applied, the relationship between structures threatened and acres burned were still nonlinear, further showing that CatBoost may be better for capturing these nonlinear relationships than parametric linear regressions even if log-scaling is taken into consideration.

Latitude and longitude of the point of fire origin were also both important variables. Based on the two-dimensional PDP of longitude and latitude overlaid on a map of the GACCs of the western United States (Fig. 5), one can see that personnel assignment tends to be highest in California GACCs, which include the Northern California GACC and the Southern California GACC. High levels of personnel assignments within California are expected considering California has more state-provided and USFS-provided resources than other states and fires in California have been associated with high levels of suppression costs and resource use in the past (Belval et al., 2020; Gebert et al., 2007; Hand et al., 2016, 2017). Moreover, despite the fact that GACCs were created to manage wildfire personnel assignment, personnel assignment partial dependence does not strictly follow GACC boundaries and is more influenced by the latitude and longitude of the point of fire origin/proximity to California. This pattern likely corresponds to the fact that California GACCs routinely share resources with neighboring GACCs.

In contrast to the variables discussed so far, fire priority is an important variable that is not a physical measurement of wildfire behavior. According to our models, fires considered to be higher priority (lower numbers) received more resourcing than fires considered to be lower priority (higher numbers) or fires with no priority being marked (denoted as −1) (Fig. 6). Fires with no priority likely occurred during times of less resource demand where fires did not have to be prioritized. It is important to note that fire priority reflects the institutional factors and the attitudes/practices of managers that affect personnel assignment yet cannot be obtained directly from wildfire simulation. Fires with similar characteristics may have completely different numbers of personnel assigned depending on what fire managers or other outside influences (such as governmental bodies) may consider important. However, while fire priority influences personnel assignment, fire priority is certainly influenced by the other independent variables as well and cannot be taken as purely political/managerial influence.

While fire priority is an important contextual variable, other contextual variables on resource supply and demand in our dataset were much less important, including national and regional preparedness levels and national and regional uncontained large fires. The characteristics of a fire are more important than other events occurring within the GACC or the country in its entirety. Fires considered to be important get the personnel required first.

4.3. Applications to fire management

The models described here provide insight into the main drivers behind personnel assignments in the recent past (2012–2020). The goal was to highlight general trends (as opposed to exact predictions for each fire) to provide historical context that could be used to guide future management decisions. Furthermore, the focus was on understanding not just the monetary cost of fire suppression, but also the cost of people's time, which can have effects on fatigue and fire suppression effectiveness. The usage of a daily scale provides a way to track how long personnel are being deployed on a fire, as opposed to predicting only the cumulative personnel assignment per fire.

Models were created to be combined with fire activities under climate change and landscape transformation in the future. Wildfire simulators could be used to generate predictions on future wildfire behavior that could then be input into these models to get an understanding of how current management practices would result in personnel usage under future conditions. Most of the variables in these models have been selected in part due to their ability to be simulated. Fire priority may be a variable about institutional influences and thus more difficult to capture, but potential in modelling the variable exists. Different GACCs will have guidelines that emphasize different physical fire characteristics in different ways. Exploration of these guidelines could allow for modeling of fire priority in the future based on other modeled fire characteristics. Information about future workload will provide insight into the sustainability of current practices and help guide decisions on how to reduce worker fatigue given lengthening fire weather seasons (Jolly et al., 2015).

Results and findings from these models are most directly applicable to the western CONUS, considering that the models were built upon data from that region. However, the methods used here could be repeated in other geographic locations that are concerned about how changing wildfire behavior may impact that area's ability to supply the necessary personnel. Certain independent variables would need to be adjusted/replaced depending on available data (such as preparedness level), but as long as there is a historical wildfire record and historical firefighting personnel assignment record, the methods here could be repeated to provide important historical context.

4.4. Potential caveats of the datasets and models

Datasets before the ROSS join and afterwards are quite different, and even personnel counts for the same fires of the two datasets do not always agree. Summing together the ground and air/overhead personnel counts shows that the sum is often greater than the total personnel count from the ICS-209-PLUS dataset (Fig. S3). Furthermore, wildfires usually, although not always, have an ICS-209 report written about them (and thus can be on the ICS-209-PLUS dataset) when the fire exceeds 100 acres in timber or 300 acres in grass or brush (St. Denis et al., 2023). As a result, only 1–2% of all wildfires are represented in this dataset (St. Denis et al., 2023). However, as mentioned previously, considering that large fires cause the majority of the firefighting costs and use the majority of personnel (St. Denis et al., 2023), we consider using these fires to be a satisfactory way to gain insight into overall firefighting personnel assignment behavior. Relative importances of independent variables can also vary as different hyperparameters are chosen due to the multicollinearity of those variables, though using CatBoost reduces the impact of multicollinearity on model fit.

Beyond just reflecting current management practices, the final datasets used for this study also reflect current physical conditions. Even if management practices do not change, other changes in environmental conditions, such as the changes in vegetation and the aforementioned climate change, will also alter the relationships between fire and personnel assignment. Susceptibility of anthropogenic structures to wildfires may also change, as studies in quantifying resilience in order to help reinforce these areas are being performed (Argyroudis et al., 2020; Tampekis et al., 2023).

It is important to note that this model is not meant for use in decision support with regards to recommending resource allocations in the future. Using this model in that fashion would require the assumption that decisions made in the past are optimal, which may not be true. Instead, this study is a retrospective analysis to help us understand what has driven resource allocation in the recent past and what that might imply for future demands on firefighting personnel.

4.5. Future work

One future plan for the models created is to simulate future fires with the Large Fire Simulator, FSim, under different climate change scenarios and to see how personnel assignment trends under current management practices may change due to climate change. FSim is a wildfire simulator that takes in information regarding landscape surface and vegetation, historical fire data, and weather data to simulate thousands of years of potential fire seasons with a focus on large fire events (Finney et al., 2011). FSim had been used with future weather data to predict future wildfire behavior under climate change. (Dye et al., 2023; McEvoy et al., 2020; Riley and Loehman, 2016). Considering that the models created here already focus on large fires, FSim would be a great match for producing future wildfire behavior to use with the models produced in this paper to provide insights into potential future demand for wildland firefighting personnel.

5. Conclusion

We found that CatBoost can produce good predictors of firefighting personnel assignment based on historical wildfire data from the years 2012–2020 within the western United States. Three models using a daily temporal resolution highlight how personnel time has been used in an effort to provide information for fatigue analysis. Our models highlighted the main drivers behind personnel assignment under current management practices, with structures threatened, acres burned, point of fire origin, and fire priority being among the most important. While contextual variables such as preparedness level and other uncontained large fires were among the least important variables, the importance of fire priority shows how factors beyond the characteristics of the fire itself are still influential in personnel assignment. Our models provide an understanding of the historical practices of personnel assignment that can be used as platform towards understanding how to manage personnel assignment under future climate change conditions.

Funding sources

This work has been supported by the Oak Ridge Institute for Science and Education (ORISE) and the Rocky Mountain Research Station through Interagency Agreement #23-IA-11221636-099 and the 2023 Aaron Kevin Rice '21 Applied Learning Award courtesy of the University of North Carolina Wilmington (UNCW). Funding sources played no role in study design, data collection, or article writing.

Disclaimer

This research was supported [in part] by the U.S. Department of Agriculture, Forest Service. The findings and conclusions in this report are those of the author(s) and should not be construed to represent any official USDA or U.S. Government determination or policy.

CRediT authorship contribution statement

Kevin Young: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation. **Erin Belval:** Writing – review & editing, Methodology, Funding acquisition, Data curation, Conceptualization. **Karin Riley:** Writing – review & editing, Methodology, Funding acquisition, Conceptualization. **Peng Gao:** Writing – review & editing, Supervision, Methodology.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Kevin Young reports financial support was provided by Oak Ridge Institute for Science and Education. Erin Belval reports a relationship with USDA Forest Service Rocky Mountain Research Station that includes: employment. Karin Riley reports a relationship with Rocky Mountain Research Station Missoula Fire Sciences Laboratory that includes: employment. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

We are grateful to Scott Zimmer, Dr. Chad Lane, and Dr. Joanne Halls for their reviews of this manuscript.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2024.122705.

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