Proc. of the European Safety and Reliability Conference (ESREL 2026)
Edited by José C. Matos, Paulo B. Lourenço, Michael Beer, Daniel Oliveira,
Edoardo Patelli, Hélder S. Sousa, Rui A. Silva and Monica Santamaria

doi: 10.3850/ESREL2026061419_esrel26-p26566-cd

An Integrated County-level Community-aware Analytics-driven Risk Evaluation (CARE) Index for Wildfire Emergency Management

Poulomee Roy
Industrial and Systems Engineering, University at Buffalo, United States. E-mail: poulomee@buffalo.edu

Sayanti Mukherjee
Industrial and Systems Engineering, University at Buffalo, United States. E-mail: sayantim@buffalo.edu

Susan Spierre Clark
Department of Environment / Sustainability, University at Buffalo, United States. E-mail: sclark1@buffalo.edu

Though wildfires have long posed a threat across the southwestern United States, their frequency and intensity are increasing due to climate change, poor land management, and the uncontrolled sprawling of population into the wildland-urban interface (WUI). For efficient wildfire mitigation and post-wildfire recovery, prioritizing resource allocation based on community resilience, wildfire severity, and experienced economic losses is essential. For example, rural communities who often lack basic capabilities and adaptive capacities need more resources and recovery efforts to manage the disaster than their wealthier counterparts. As resource and recovery efforts are managed by local authorities across counties, understanding the county-level risk in wildfire emergency management (WEM) is instrumental to advance risk-informed community- wildfire resource allocations. Therefore, this study aims to develop a county-level **C**ommunity-aware **A**nalytics-driven **R**isk **E**valuation (**CARE**) index for WEM leveraging advanced machine learning algorithms. To that end, we collected data from multiple publicly available sources from 2015 to 2022 on wildfire hazard exposure (e.g., information on past wildfire incidents), social vulnerability of communities (e.g., socioeconomic factors, demography) and physical/economic damage caused by wildfires (e.g., structural damage, post-wildfire resource allocations) to predict WEM-CARE index under various scenarios. For our case study, we considered the southwestern US states including California (CA), Arizona (AZ), Colorado (CO), Nevada(NV), Utah (UT), and New Mexico (NM) that are exposed to frequent and severe wildfire events. Our preliminary insights suggest that although urban counties like Los Angeles are highly exposed to wildfire events, the remote, mountainous counties like Plumas, CA are more vulnerable to wildfire and require greater attention in recovery efforts due to their socio-economic attributes. The outcome also identifies socio-economic and demographic factors that contribute to counties' vulnerability to wildfire, which is an understudied aspect of current research.

Keywords: Wildfire emergency management risk, Targeted resource allocation, Statistical learning, Community-focused decision-making.

Wildfires have increased significantly in recent decades due to climate change and the unrestricted expansion of wildland-urban interface (WUI) communities in the United States (UC Merced School of Engineering, 2025; NASA Earth Science, 2023). Studies have shown that wildfire damage extends far beyond the fire's direct impact. Often, the restoration, recovery, and rebuilding of the communities take years, even decades, due to lack of efficient disaster preparedness and recovery efforts (McWethy et al., 2019).

Enhancing wildfire emergency management (WEM) is critical to improving the preparedness of WUI communities Kapucu (2014). This requires a better understanding, characterization, and prediction of the interactions between wildfire propagation, the critical infrastructure systems, humans, and the protective actions that shape the extent of physical, social, and economic impacts on the socially vulnerable population. From a governance perspective of WEM, counties often play a pivotal role in post-wildfire restoration and recovery. County administrations serve as intermediaries between state and federal agencies and local disaster management and response teams (Colonico et al., 2022). Reports have revealed that counties often bear responsibility for removal of debris, coordinating evacuations with the emergency management team, providing immediate shelter, long-term land management, and community rebuilding, under several socioeconomic and administrative constraints (Fraser et al., 2022). Furthermore, the limited resources and lack of disaster preparedness make the WEM even more challenging. Studies have shown that disaster preparedness, social vulnerability and community resilience strongly influence community's recovery and rebuilding (Paveglio et al., 2016; de Diego et al., 2023). Therefore, the county administration needs a clear understanding of the WEM risk to support both early-stage preparedness and planning for post-fire resource allocation.

While progress has been made in predicting wildfire propagation risk (Roy et al., 2025; Masoudvaziri et al., 2020, 2021), major limitations still persist in understanding the complex interactions among wildfires, critical infrastructure systems, socially-vulnerable populations, and WEM practices. For example, the widely-used National Risk Index (NRI) developed by the Federal Emergency Management Administration (FEMA) identifies US communities most at wildfire risk, using data on wildfire frequency, expected annual losses, social vulnerability, and community resilience (Zuzak et al., 2021). However, it is a static index and fails to account for the dynamic characteristics of the fire spread or the post wildfire resource allocation challenges, thereby making it inadequate to inform WEM practices.

On the other hand, majority of the previous studies focusing on wildfire risk assessment only considered the hazard exposure and the consequences in terms of infrastructure damages, overlooking the social vulnerability of the population (Holden and Jolly, 2011; Holsinger et al., 2016; Finney et al., 2011; Fox et al., 2018). Moreover, despite providing a detailed overview of fire behavior, these studies fail to offer any insight into community resilience, which significantly impacts recovery, disaster preparedness, and the community's ability to cope with disasters. Although, recently there has been a growing literature in understanding how communities are disproportionately impacted by the wildfires (Davies et al., 2018; Masri et al., 2021; Thomas et al., 2022; Roy and Mukherjee, 2025), these human-centric aspects are not integrated into the wildfire risk assessment. Thus, when these traditional wildfire risk models are used to inform WEM decisions, they fail to account for the community needs and thus cannot prioritize recovery strategies integrating the human-centric aspects.

To summarize, although wildfire risk assessment received significant attention from the scientific community, assessing the risk of WEM from a holistic perspective is not yet well understood. Specifically, the existing wildfire risk studies are conducted in siloes either focusing on the wildfire spread or infrastructure damages or impact to the communities. In this paper, we aim to address this gap by developing an integrated, **C**ommunity-aware **A**nalytics-driven **R**isk **E**valuation (**CARE**) index for WEM. To that end, since risk is multidimensional, (Amundrud et al., 2017; International Energy Agency, 2022) we formulate the CARE index for WEM as a function of wildfire hazard and exposure (historical frequency and probability of wildfire), the social vulnerability of the communities (measured by socioeconomic and demographic attributes), and the physical/economic damage caused by wildfire (measured by structural damage and the consequence of post wildfire resource allocation).

For our study, we considered the southwestern US states—California (CA), Arizona (AZ), Colorado (CO), Nevada (NV), Utah (UT), and New Mexico (NM) due to their extensive wildfire exposure and diverse demographics. We integrated county-level historical wildfire impact and resource allocation data from 2015 to 2022, along with census data on socio-demographics, to develop the CARE index leveraging data-driven, advanced machine learning algorithms.

1. Methodology

To develop the WEM-CARE index, we propose a unique data-driven framework to quantify wildfire risk across counties, accounting for historical wildfire impacts and community resilience. Figure 1 shows the data-driven framework, from data collection and pre-processing to exploratory data analysis, model development, and inference for the CARE index.

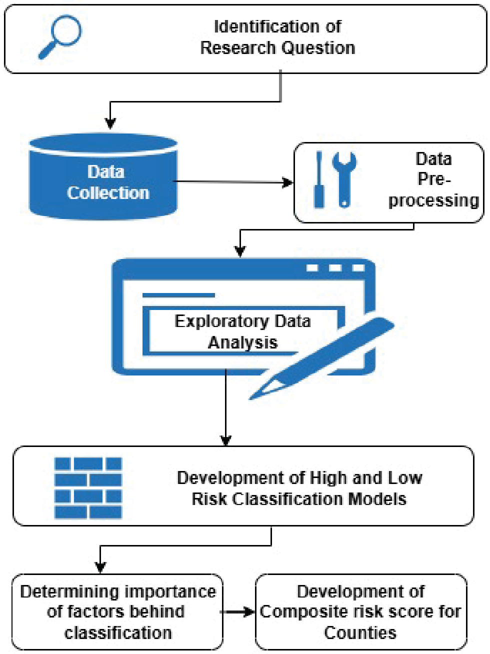

Fig. 1. Framework of the Study

1.1. *Data Preparation*

Data preparation consists of multiple steps: data collection, data pre-processing, and exploratory data analysis.

1.1.1. *Data Collection*

The wildfire impact and demographic data have been collected from the following sources:

Incident Command Systems (ICS): The incident level data of historic wildfires containing information about their severity, physical and economic impacts of wildfires on the infrastructure and communities, and information on the post-fire recovery and resource allocation is obtained for the states of California (CA), Arizona (AZ), Colorado (CO), Nevada (NV), Utah (UT) and New Mexico (NM) from SIT209 database published by the Incident Command Systems of the US (Wildfire.gov, 2022). The data contains 34 features and 996 incident records from 2015 to 2022.

US Census Data: From the US Census Bureau (US Census, 2024), a total of 26 county-level socio-demographic and economic variables are obtained for the six states from 2015 to 2022. Examples of variables include ethnicity, race, and the proportion of the educationally and economically disadvantaged population. These variables are used to measure social vulnerability and community resilience in our analysis. The community resilience and Social Vulnerability indices do not focus on any specific disaster; therefore, all vulnerability indicators are given equal weight. In our study, we weighed the socio-demographic variables based on their contribution to predicting high and low wildfire impacts.

1.1.2. *Data Pre-processing*

After collecting and consolidating the dataset, we processed the data using data imputation, cleaning and standardizing it.

Data Imputation and Cleaning: As there are multiple missing values in the US Census dataset, we adopted various data imputation techniques, including a moving average and an interpolation-based method. For the ICS data, which is more dynamic, we have adopted machine learning (ML) based methods to impute the missing values. In ML-based imputation, the variable with missing values is treated as the response variable, and all other variables serve as predictors for imputing the missing values (Hong and Lynn, 2020).

Standardizing the Dataset: Prior to implementing the ML algorithms, all the variables are standardized using a min-max scalar function to ensure the model is not biased by any one variable with higher values.

1.1.3. *Exploratory Data Analysis*

Figure 2 displays the quantile distribution of wildfire severity variables (e.g., burnt area) and the impact to the infrastructure and communities (e.g., structural damage, fatalities, cost for recovery). The figure shows that after the third quantile, the

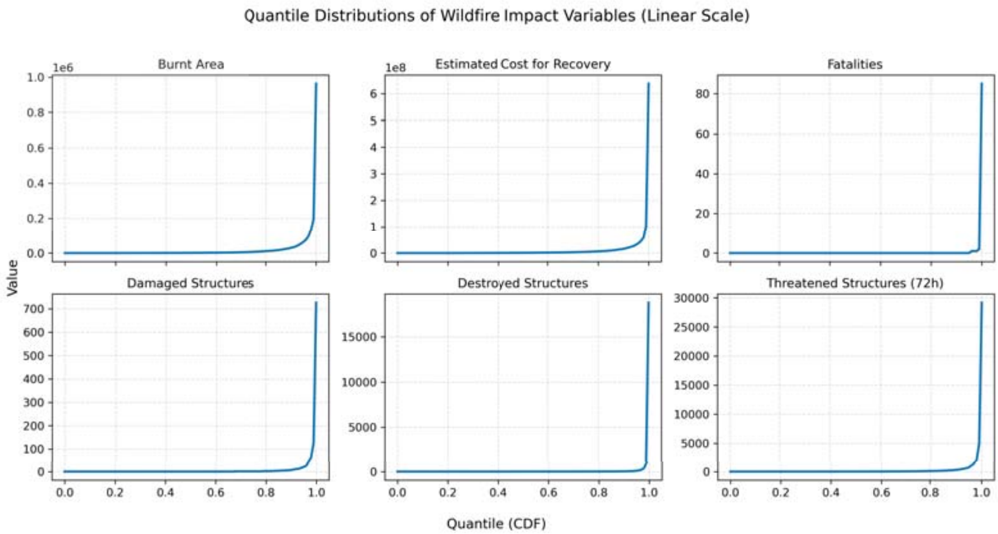

Fig. 2. Quantile Distribution of Wildfire Impact

variables exhibit steep growth, indicating a right-skewed distribution. The fourth quantile of all variables (high-impact incidents) shows a steep increase in impact compared with the first three quantiles (low-impact incidents).

1.1.4. *Determining the Response Variable*

After exploratory data analysis, we observed that wildfire severity and impact variables, such as *Burnt Area, Estimated Cost for Recovery, Fatalities, and Structures Damaged and Destroyed*, exhibit similar distributions.

This is an expected observation as severe wildfires generally cause more damage. We treated the *Estimated Cost for Recovery* as the response variable and the others as predictors. The *Estimated Cost for Recovery* accounts for the cost of the restoration operation and the financial allocation for post-wildfire recovery. This variable depicts the economic impact and is directly related to the decision-making process of emergency management. Therefore, for predicting the WEM-CARE index, this variable serves as the response variable. Owing to the wildfire severity being significantly higher in the 3rd quantile, we divided the incident-level data into two cohorts: incidents reporting $\geq$75 percentile *Estimated Cost for Recovery* are labeled the high-impacted cohort, and the remaining data are labeled the low-impacted cohort. Based on this classification, we sought to identify the driving socio-economic and wildfire impact factors of risk. We also adopted a correlation screening method to reduce dimensionality of the data (Mukherjee and Nateghi, 2017).

1.2. *Development of the Risk Models*

Supervised learning theory is leveraged to characterize the *Estimated Cost for Recovery*. Broadly speaking, the goal of supervised learning is to estimate a function capable of predicting a statistical moment of a target variable (e.g., *Estimated Cost for Recovery*) conditioned on one or more predictor variables (e.g, various socioeconomic variables, structural failures, recovery aspects, burnt area etc.), such that the loss function of interest (measuring the distance between the predictions and the observed values) is minimized. Supervised statistical learning methods can be parametric, semi-parametric or non-parametric. Parametric models generally assume a particular functional form that relates the input variables to the response. The assumed functional forms ease estimation and model interpretation but come at the cost of predictive accuracy, since the assumptions (such as normality and linearity) often do not hold in real data. Non-parametric models make few assumptions about the distribution of the response variable or the shape of the function relating the response to the predictors. Instead, they use the data in novel ways to approximate the dependencies. Their predictive power is generally superior to that of parametric models because they better approximate the true functional forms. Moreover, non-parametric methods are data-intensive and highly dependent on data quality. In this study, we implemented a classification algorithm to predict the high- and low-impact classes based on the response variable *Estimated Cost for Recovery*. We trained libraries of models starting from logistic regression, support vector machine (SVM), k-nearest neighbors (KNN), random forest (RF), XG boost (XG Boost), gradient boost (GB), and light gradient boosting machine (LGBM). After validating the models using a percentage holdout cross-validation, XGBoost classification was the best.

XGBoost is a very effective boosting algorithm that grows sequentially to optimize predictive performance. It is unique for its sequential, slow learning process, which leads to higher predictive accuracy. It uses techniques like histogram-based splitting, leaf-wise growth, and feature bundling (Breiman, 2000; Chen et al., 2015).

Model Performance Evaluation and Selection: The generalization performance of a predictive model hinges on its ability to minimize both bias and variance. Cross-validation is a resampling technique for balancing bias and variance. We used an 80-20 holdout cross-validation, where the model is trained on 80% of the data held out at random and tested on the remaining 20%. This process is repeated 20 times, and training and test performance are computed by averaging the performance evaluations across iterations.

Predictive accuracy vs. model interpretability: Flexible non-parametric methods generally have higher predictive power than the parametric models. The improved predictive power, however, comes at the cost of ease of interpretability (Hastie et al., 2008). Partial dependence plots (PDPs) are efficient methods for variable inference and feature importance in non-parametric models. PDPs help in understanding the individual effects of the predictor variables (x_j) on the response variable, ceteris paribus (i.e., controlling for all other predictors). Feature importance indicates the contribution of a predictor variable to the classification model's predictions (Hastie et al., 2008). In our study, the contributions of predictor variables (i.e., normalized feature importance) in the XGBoost classification model are used to weight variables to develop the WEM-CARE index, which is calculated as the weighted sum of all normalized wildfire-impact variables (Mehta et al., 2016).

$$\text{Risk}_i = \sum_{j=1}^{p} w_j \, \tilde{X}_{ij}, \tag{1}$$

where $\tilde{X}_{ij}$ represents the normalized value of variable j for spatial unit i, $w_j \geq 0$ denotes the weight assigned to indicator j based on the feature importance, and $\sum_{j=1}^{p} w_j = 1$.

2. Results

2.1. *Model Performance Evaluation*

Comparing training and test performance, we observe that ensemble methods and tree-based models clearly outperform linear models such as logistic regression in both predictive accuracy and goodness of fit.

Table 1. Training performance for high vs. low wildfire cost classification.

Model	Acc.	Prec.	Rec.	F1
XGBoost	0.99	0.98	0.95	0.94
LightGBM	0.97	0.91	0.92	0.95
Random Forest	0.97	0.92	0.97	0.95
Gradient Boosting	0.96	0.96	0.89	0.93
SVM (RBF, scaled)	0.92	0.82	0.84	0.83
Logistic Reg. (scaled)	0.89	0.77	0.82	0.79
KNN (scaled)	0.79	0.87	0.19	0.31

Note: Metrics are calculated on training data by segregating and high and low impact of wildfires by 75 percentile of `Estimated Cost for Recovery`.

The ensemble models exhibit consistently improved performance across the training and

Table 2. Predictive accuracy for high vs. low wildfire cost classification.

Model	Acc.	Prec.	Rec.	F1
Gradient Boosting	0.93	0.90	0.80	0.85
Random Forest	0.92	0.87	0.82	0.84
XGBoost	0.92	0.88	0.80	0.84
LightGBM	0.91	0.85	0.78	0.81
Logistic Reg. (scaled)	0.89	0.80	0.75	0.78
SVM (RBF, scaled)	0.85	0.72	0.62	0.67
KNN (scaled)	0.78	0.75	0.15	0.25

Note: Metrics are computed on a held-out test set using a 75th percentile cutoff to define high-cost wildfire events based on `Estimated Cost for Recovery`.

test datasets, suggesting they effectively balance bias and variance, leading to better generalization. Random Forest, LightGBM, and XGBoost achieve significantly improved performance across training and test accuracy, precision, recall, and F1 score compared with logistic regression, SVM, and KNN. We have evaluated the train and test accuracy after performing percentage hold-out cross-validation. Among the ensemble models, XGBoost achieves the highest training and predictive accuracy (directionally higher than the other models) and is selected as the best model.

2.2. *Model Inference and Feature Importance*

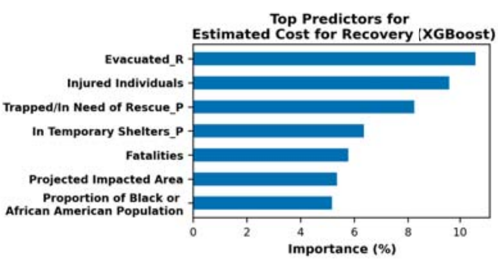

Fig. 3. Driving Factors behind Prediction

To understand each feature's contribution to the selected model's predictive accuracy, we conducted a feature selection analysis using XGBoost. To that end, in this study, feature importance refers to the extent to which each feature contributes to predicting the *Estimated Cost for Recovery* (i.e., the WEM risk) and is thus used as a risk-weighting factor for the respective predictors when developing the CARE index (Zhao and Henriksson, 2016).

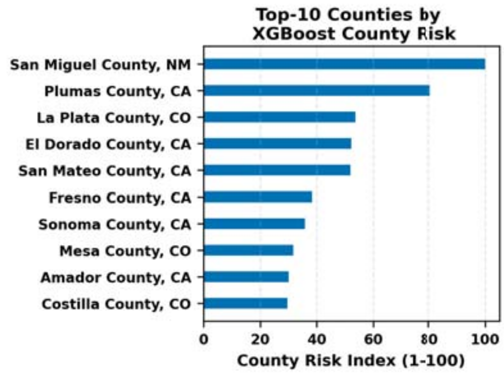

Fig. 4. Top-10 High-Risk Counties across Southwestern United States

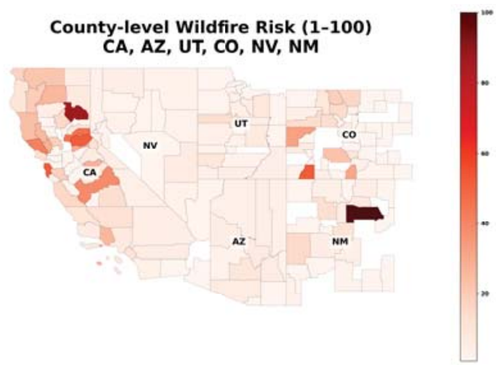

Fig. 5. County-level Composite Risk Index

Figure 3 shows that the driving factors of high and low-impact counties consist of a combination of both wildfire impacts and socio-demographic composition of the counties. Factors like *number of evacuated, injured, trapped individuals, fatalities, projected impacted area* show the importance of the wildfire impact/consequence variables in predicting the risk of WEM in the counties experiencing high and less severe wildfires. On the other hand, *proportion of below poverty level population and Black or African American population* emerges as a significant socio-demographic predictor, illustrating the importance of social vulnerability in predicting the WEM risk.

The spatial distribution of the WEM risk shows that high-risk counties are unevenly distributed across CA, AZ, NV, CO, UT, and NM (as shown in Figure 5). Because the WEM-CARE index is founded on both wildfire impacts/consequence and social vulnerability, we observe that the counties that experienced severe wildfires has a higher risk index than those that experience less severe wildfires.

Complementing the spatial distribution of the WEM-CARE index, Figure 4 shows the top-10 high-risk counties in the southwestern states. San Miguel County, NM, and Plumas County, CA, top the list. In addition, El Dorado and San Mateo counties in CA also have a higher CARE index. The dominance of CA in the upper risk tiers is attributed to the state's widespread wildfire exposure, coupled with a lack of community resilience, especially among those who reside in the wildland-urban interface (WUI).

3. Conclusion

Though this study developed a comprehensive risk index that integrates community-level hazard, exposure, and vulnerability, it consists of some limitations. In this particular framework, we did not modify the predictors or the factors to understand how that affects the overall ranking of the counties. Instead we developed the risk index based upon the weighted socio-demographic and hazard-related factors implementing the data-driven models. However, by aligning the risk-propensity framework with the administrative framework of county jurisdiction, the risk index will streamline decision-making for advanced disaster preparedness and targeted resource allocation based on community needs. Overall, this study advances the data-driven risk framework by designing and operationalizing a multidimensional risk index that provides scalable, policy-relevant insights.

References

Amundrud, Ø., T. Aven, and R. Flage (2017). How the definition of security risk can be made compatible with safety definitions. Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability 231(3), 286–294.

Breiman, L. (2000). Some infinity theory for predictor ensembles. Technical report, Citeseer.

Chen, T., T. He, M. Benesty, V. Khotilovich, Y. Tang, H. Cho, K. Chen, R. Mitchell, I. Cano, T. Zhou, et al. (2015). Xgboost: extreme gradient boosting. R package version 0.4-2 1(4), 1–4.

Colonico, M., A. Tomao, D. Ascoli, P. Corona, F. Giannino, J. V. Moris, R. Romano, L. Salvati, A. Barbati, et al. (2022). Rural development funding and wildfire prevention: Evidences of spatial mismatches with fire activity. Land Use Policy 117(106079), 1–9.

Davies, I. P., R. D. Haugo, J. C. Robertson, and P. S. Levin (2018). The unequal vulnerability of communities of color to wildfire. PloS one 13(11), e0205825.

de Diego, J., M. Fernández, A. Rúa, and J. D. Kline (2023). Examining socioeconomic factors associated with wildfire occurrence and burned area in galicia (spain) using spatial and temporal data. Fire Ecology 19(1), 18.

Finney, M. A., C. W. McHugh, I. C. Grenfell, K. L. Riley, and K. C. Short (2011). A simulation of probabilistic wildfire risk components for the continental united states. Stochastic Environmental Research and Risk Assessment 25(7), 973–1000.

Fox, D., P. Carrega, Y. Ren, P. Caillouet, C. Bouillon, and S. Robert (2018). How wildfire risk is related to urban planning and fire weather index in se france (1990–2013). Science of the total environment 621, 120–129.

Fraser, A. M., M. V. Chester, and B. S. Underwood (2022). Wildfire risk, post-fire debris flows, and transportation infrastructure vulnerability. Sustainable and Resilient Infrastructure 7(3), 188–200.

Hastie, T., R. Tibshirani, and J. Friedman (2008). Overview of supervised learning. In The elements of statistical learning: Data mining, inference, and prediction, pp. 9–41. Springer.

Holden, Z. A. and W. M. Jolly (2011). Modeling topographic influences on fuel moisture and fire danger in complex terrain to improve wildland fire management decision support. Forest Ecology and Management 262(12), 2133–2141.

Holsinger, L., S. A. Parks, and C. Miller (2016). Weather, fuels, and topography impede wildland fire spread in western us landscapes. Forest ecology and management 380, 59–69.

Hong, S. and H. S. Lynn (2020). Accuracy of random-forest-based imputation of missing data in the presence of non-normality, non-linearity, and interaction. BMC medical research methodology 20(1), 199.

International Energy Agency (2022). Climate hazard assessment.

Kapucu, N. (2014). Collaborative governance and disaster recovery: the National Disaster Recovery Framework (NDRF) in the US. In Disaster recovery, pp. 41–59. Springer.

Masoudvaziri, N., P. Ganguly, S. Mukherjee, and K. Sun (2020, November). Integrated Risk-informed Decision Framework to Minimize Wildfire-induced Power Outage Risks: A County-level Spatiotemporal Analysis. 30th European Safety and Reliability Conference. Accessed on February 06, 2026.

Masoudvaziri, N., P. Ganguly, S. Mukherjee, and K. Sun (2021). Impact of geophysical and anthropogenic factors on wildfire size: A spatiotemporal data-driven risk assessment approach using statistical learning. Stochastic Environmental Research and Risk Assessment, 1103–1129.

Masri, S., E. Scaduto, Y. Jin, and J. Wu (2021). Disproportionate impacts of wildfires among elderly and low-income communities in california from 2000–2020. International journal of environmental research and public health 18(8), 3921.

McWethy, D. B., T. Schoennagel, P. E. Higuera, M. Krawchuk, B. J. Harvey, E. C. Metcalf, C. Schultz, C. Miller, A. L. Metcalf, B. Buma, et al. (2019). Rethinking resilience to wildfire. Nature Sustainability 2(9), 797–804.

Mehta, H. B., V. Mehta, C. J. Girman, D. Adhikari, and M. L. Johnson (2016). Regression coefficient–based scoring system should be used to assign weights to the risk index. Journal of clinical epidemiology 79, 22–28.

Mukherjee, S. and R. Nateghi (2017). Climate sensitivity of end-use electricity consumption in the built environment: an application to the state of florida, united states. Energy 128, 688–700.

NASA Earth Science (2023). Wildfires and climate change.

Paveglio, T. B., T. Prato, C. Edgeley, and D. Nalle (2016). Evaluating the characteristics of social vulnerability to wildfire: Demographics, perceptions, and parcel characteristics. Environmental Management 58(3), 534–548.

Roy, P. and S. Mukherjee (2025). Burning inequities: Comparative analysis of socioeconomic drivers for post-wildfire resource allocation in the southwestern us states.

Roy, P., S. Mukherjee, and P. Sankaran (2025). Blaze track: Developing dynamic wildfire risk maps leveraging modis satellite imagery and advanced ai algorithms. In IISE Annual Conference. Proceedings, pp. 1–6. Institute of Industrial and Systems Engineers (IISE).

Thomas, A. S., F. J. Escobedo, M. R. Sloggy, and J. J. Sanchez (2022). A burning issue: Reviewing the socio-demographic and environmental justice aspects of the wildfire literature. PLoS One 17(7), e0271019.

UC Merced School of Engineering (2025). Wildfire disasters surged in the past 10 years, study shows.

US Census (2024). The United States Census Bureau. Accessed: 2024-07-30.

Wildfire.gov (2022). Sit-209: Wildland fire application information portal.

Zhao, J. and A. Henriksson (2016). Learning temporal weights of clinical events using variable importance. BMC medical informatics and decision making 16(Suppl 2), 71.

Zuzak, C., E. Goodenough, C. Stanton, M. Mowrer, N. Ranalli, D. Kealey, and J. Rozelle (2021). National risk index technical documentation. Federal Emergency Management Agency, Washington, DC 37.