Assessing Wildfire Drivers in the Marshall Fire Using Remote Sensing and Random Forest

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Abstract: This study focuses on the 2021 Marshall Fire occurring in the Wildland-Urban Interface (WUI) of Colorado, USA, aiming to quantify fire driving factors and devise targeted mitigation strategies. Based on multi-source datasets including ERA5 meteorological reanalysis, MODIS NDVI, SRTM terrain and NLCD land cover products, nine environmental driving factors covering topography, meteorology and vegetation were selected. A random forest model was adopted to quantify the contribution of each factor to the spatial distribution of wildfire and divide fire risk grades for differentiated risk reduction management. The model attained an overall classification accuracy of 93.7%, revealing favorable simulation performance. Topographic elevation served as the dominant driving factor with an importance value of 0.452, followed by relative humidity (0.140) and wind speed (0.116). Burned regions were characterized by higher elevation, lower ambient relative humidity and steeper terrain gradients. Although the regional averaged wind speed was marginally higher in unburned zones, valley-induced localized extreme gusts made wind speed a vital fire-controlling factor. According to factor spatial differentiation, the study partitions the study area into high, medium and low fire risk zones and proposes corresponding risk reduction measures. The research results can support wildfire risk mapping, risk zoning and differentiated prevention & risk reduction management for North American WUI regions.

Keywords: Wildland-Urban Interface Wildfire; Random Forest; Driving Factor; Marshall Fire; Risk Zoning; Disaster Reduction

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1 Introduction

Wildfires have become increasingly frequent and destructive under the influence of climate change, prolonged droughts, and extreme weather events. The impacts are particularly severe in WUI areas, where human settlements are directly adjacent to flammable vegetation. As urban expansion continues, wildfire disasters in WUI regions pose growing threats to human lives, infrastructure, and ecosystems. Therefore, identifying the environmental factors that drive wildfire occurrence is essential for effective disaster risk reduction and land-use planning.

Previous studies have shown that wildfire occurrence is influenced by a combination of topographic, meteorological, and vegetation-related factors. Elevation, slope, and aspect can affect local microclimatic conditions and fire spread patterns [1, 2]. Meteorological variables such as temperature, humidity, and wind speed play important roles in fuel drying and fire propagation [3, 4]. In addition, remote sensing indicators such as the Normalized Difference Vegetation Index (NDVI) have been widely used to characterize vegetation conditions and fuel availability [5]. With the development of satellite observations and cloud-

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computing platforms, machine-learning approaches, particularly Random Forest (RF), have become effective tools for wildfire susceptibility assessment and driving-factor analysis because of their ability to model complex nonlinear relationships and quantify variable importance [6, 7].

Although considerable progress has been made, several limitations remain. Many studies focus on individual factors rather than the combined effects of topography, meteorology, and vegetation. Furthermore, wildfire susceptibility studies often emphasize model prediction while providing limited guidance for practical disaster risk reduction. Research on the 2021 Marshall Fire is also relatively limited despite its significance as one of the most destructive WUI wildfire events in Colorado.

To address these gaps, this study investigates the Marshall Fire as a representative WUI wildfire case. Multi-source datasets, including ERA5-Land meteorological data, MODIS NDVI products, and SRTM topographic data, are integrated to construct environmental driving factors. A Random Forest model is then employed to quantify the relative importance of these factors and identify the dominant controls on wildfire occurrence.

The objectives of this study are to: (1) analyze the environmental characteristics associated with the Marshall Fire; (2) quantify the contributions of topographic, meteorological, and vegetation factors using a Random Forest model; and (3) develop wildfire risk zoning and corresponding risk reduction strategies based on the identified driving mechanisms. The results provide scientific support for wildfire risk assessment and disaster risk reduction planning in WUI regions under changing climate conditions.

2 Study Area Overview

The study area is located in Boulder County, Colorado, United States, along the eastern foothills of the Rocky Mountains (39.97°–40.07°N, 105.22°–105.10°W). This region forms a typical WUI, where residential communities are directly adjacent to grasslands, shrublands, and other natural vegetation. Elevation ranges from approximately 1,530m to 1,726m above sea level, characterized by gently rolling terrain and foothill landscapes.

The area experiences a semi-arid continental climate with low annual precipitation, dry winters, and strong seasonal winds. In particular, downslope Chinook winds originating from the Rocky Mountains frequently generate extreme wind events during winter months. Combined with prolonged drought conditions and low relative humidity, these climatic characteristics substantially increase wildfire susceptibility and accelerate fire spread. Vegetation within the region mainly consists of short-grass prairie, xeric shrublands, and fragmented urban green spaces, providing abundant fine fuels that can rapidly ignite under dry and windy conditions.

The study focuses on the 2021 Marshall Fire, one of the most destructive wildfires in Colorado's recorded history. The fire ignited on 30 December 2021 under exceptional drought and extreme wind conditions. Within a few hours, the fire spread rapidly through suburban communities including Louisville and Superior, burning approximately 6,026 acres (24.39 km^2), destroying more than 1,000 structures, and causing losses exceeding US$2 billion. The event resulted in the evacuation of approximately 37,500 residents and highlighted the increasing vulnerability of expanding WUI communities to climate-driven wildfire hazards.

Several factors make the Marshall Fire an ideal case for wildfire driving-factor analysis. First, the fire occurred within a highly developed WUI environment where natural vegetation and human settlements coexist. Second, the event was strongly influenced by the interaction of topography, vegetation conditions, and extreme meteorological factors, providing an opportunity to examine their combined effects on wildfire occurrence. The availability of high-quality remote sensing, meteorological reanalysis, and land-cover datasets enables quantitative assessment of environmental controls on wildfire distribution.

Therefore, the Marshall Fire provides a representative case for investigating the environmental drivers of wildfire occurrence in North American WUI regions and offers valuable insights for wildfire risk assessment, land-use planning, and disaster risk reduction strategies under changing climatic conditions.

3 Data Sources and Preprocessing

3.1 Meteorological Data

Meteorological variables were extracted from ECMWF ERA5-Land hourly reanalysis dataset via the GEE platform, with an original spatial resolution of 9 km. Five parameters were chosen: near-surface air temperature, surface skin temperature, 10 m wind speed, relative humidity and surface soil moisture. Original hourly data were averaged into daily values and clipped to the study boundary. Daily averaged meteorological data were used for macroscopic spatial driving analysis, while instantaneous extreme valley wind effects were interpreted qualitatively in the discussion section due to data limitation.

3.2 Vegetation NDVI Data

Vegetation conditions were characterized using the MODIS MOD13Q1 product with a spatial resolution of 250 m and a temporal resolution of 16 days. NDVI was selected as an indicator of vegetation cover and fuel conditions. Images corresponding to the study period were acquired and preprocessed in Google Earth Engine (GEE), including cloud masking, noise reduction, and spatial clipping. The calculation of NDVI is described in Section 4.2.

NDVI images corresponding to the time of the fire were selected, and raster data were exported after cloud masking and noise reduction processing in GEE. Due to the fixed cycle of satellite products, this 16-day composite product was used to characterize the wetness and dryness of vegetation and the overall level of vegetation cover in the area before and after the fire. [8]

3.3 Topographic Data

Elevation, slope, and aspect were extracted from SRTM 30 m DEM data, with the original data sourced from NASA. To ensure consistent spatial scale, the topographic raster was resampled to 250 m, maintaining resolution consistency with the vegetation data.

3.4 Land Use Data and Variable Selection Rationale

Land cover data was obtained from the 2020 National Land Cover Database (NLCD) to characterize the surface fuel types across the WUI. However, after rigorous preprocessing and correlation analysis, this variable was ultimately excluded from the final Random Forest modeling.

Preliminary statistical tests, including Pearson correlation and multicollinearity diagnostics, indicated a weak explanatory power of the raw land cover classes for the specific spatial pattern of the Marshall Fire. This is likely attributed to two factors specific to this event: first, the fire occurred during winter when herbaceous vegetation (grasslands) was uniformly dry and senescent across different land cover classes; second, the extreme wind conditions overwhelmed the moderating effect of local land use on fire spread.

Furthermore, to maintain model parsimony and avoid potential noise from categorical variables with low variance in the burned perimeter, the decision was made to focus on continuous environmental drivers (meteorology, topography, and vegetation moisture). Consequently, the final modeling dataset comprised nine key variables, excluding land use, to quantitatively assess the dominant environmental controls on wildfire occurrence.

3.5 Unified Data Preprocessing

All data were uniformly converted to the WGS84 geographic coordinate system with a spatial resolution of 250m, and the boundaries were cropped to the study area. The data were then fused to generate a comprehensive driving factor raster, which includes 9 variables: NDVI, wind speed, soil moisture, air temperature, relative humidity, elevation, slope, aspect, and surface temperature.

4 Research Methods

4.1 Research Framework

This study employed a remote sensing and machine learning framework to identify the key environmental drivers influencing the spatial distribution of the 2021 Marshall Fire. The workflow consisted of four major stages:

1. Multi-source data acquisition and preprocessing;
2. Wildfire sample extraction using burn severity indicators;
3. Construction of environmental driving-factor datasets;
4. Wildfire modelling and importance assessment using a Random Forest (RF) classifier.

First, meteorological, vegetation, and topographic datasets were collected from publicly available sources, including ERA5-Land reanalysis products, MODIS vegetation products, and SRTM digital elevation models. All datasets were resampled to a common spatial resolution of 250 m and projected into a unified coordinate system.

Second, burned and unburned samples were identified based on the differenced Normalized Burn Ratio (dNBR), which enabled the construction of a binary wildfire occurrence dataset. Third, nine environmental variables were extracted and integrated into a unified geospatial database. Finally, a Random Forest model was trained to quantify the relative contribution of each factor to wildfire occurrence and to evaluate the predictive performance of the model.

4.2 Environmental Variable Construction

Based on previous wildfire studies, nine environmental variables representing topographic, meteorological, and vegetation conditions were selected as explanatory variables for wildfire occurrence modelling.

Topographic variables included elevation (Elev), slope (Slp), and aspect (Asp), which were derived from the SRTM digital elevation model (DEM). Meteorological variables were obtained from the ERA5-Land dataset, including air temperature (Ta), surface temperature (Ts), relative humidity (RH), wind speed (Ws), and soil moisture (SM).

Vegetation conditions were represented by the Normalized Difference Vegetation Index (NDVI), calculated from MODIS MOD13Q1 imagery as:

$$NDVI = \frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + \rho_{Red}} \tag{1}$$

where:

ρNIR = surface reflectance in the near-infrared band;

ρRed = surface reflectance in the red band;

NDVI = Normalized Difference Vegetation Index.

Higher NDVI values indicate denser vegetation cover and greater fuel availability, whereas lower values generally represent sparse vegetation or non-vegetated surfaces.

All environmental variables were resampled to a common spatial resolution of 250 m and integrated into a multi-band raster dataset for subsequent modelling.

4.3 Burned Area Extraction

To identify wildfire-affected areas, the Normalized Burn Ratio (NBR) was calculated using pre-fire and post-fire satellite imagery. NBR is widely used for burn severity assessment because it is sensitive to vegetation loss and post-fire surface changes. [9]

The NBR was calculated as:

$$NBR = \frac{\rho_{NIR} - \rho_{SWIR}}{\rho_{NIR} + \rho_{SWIR}} \tag{2}$$

where:

ρNIR = surface reflectance in the near-infrared band;

ρSWIR = surface reflectance in the shortwave infrared band;

NBR = Normalized Burn Ratio.

The differenced Normalized Burn Ratio (dNBR) was then calculated as:

$$dNBR = NBR_{pre} - NBR_{post} \tag{3}$$

where:

dNBR = differenced Normalized Burn Ratio;

NBRpre = NBR value derived from the pre-fire image;

NBRpost = NBR value derived from the post-fire image.

Pixels with dNBR values greater than 0.27 were classified as burned areas according to commonly adopted wildfire burn-severity thresholds. [10] A binary wildfire mask was subsequently generated, where burned pixels were assigned a value of 1 and unburned pixels a value of 0.

Based on the generated wildfire mask, a total of 2,288 samples were randomly extracted, including 945 burned samples and 1,343 unburned samples. These samples were used as the dependent variable in the Random Forest model.

4.4 Random Forest Modelling and Variable Importance Analysis

Random Forest (RF) is an ensemble machine-learning algorithm that constructs multiple decision trees through bootstrap sampling and random feature selection. Compared with traditional statistical approaches, RF can effectively capture nonlinear relationships and interactions among environmental variables, [11] making it suitable for wildfire susceptibility analysis.

In this study, the RF model was implemented using the Scikit-Learn library in Python. A total of 2,288 samples, including burned and unburned pixels, were randomly divided into training (70%) and testing (30%) datasets. The number of decision trees was set to 500 to ensure model stability and reproducibility.

Nine environmental variables were used as model inputs, including elevation, slope, aspect, air temperature, surface temperature, relative humidity, wind speed, soil moisture, and NDVI. The wildfire occurrence dataset derived from the dNBR-based burned area extraction served as the dependent variable.

Model performance was evaluated using Overall Accuracy (OA), Area Under the Receiver Operating Characteristic Curve (AUC), and F1-score. These indicators were used to assess the classification capability and predictive reliability of the RF model.

To identify the dominant environmental controls on wildfire occurrence, feature importance values generated by the RF model were analyzed. Variables with higher importance values were considered to have stronger contributions to wildfire prediction and were used to interpret wildfire-driving mechanisms.

5 Results and Analysis

5.1 Model Accuracy Evaluation

The overall classification accuracy of the random forest model was 93.7%, and the accompanying AUC and F1 scores were both excellent, indicating that the selected nine environmental factors can well explain the spatial distribution pattern of the Marshall Fire, and the model results have high reliability.

5.2 Ranking of Driving Factor Importance

Based on the random forest experiment, the data in Table 1 was obtained. The analysis is as follows: elevation was the primary controlling factor for fire in this study area, contributing over 45%; Relative Humidity and regional wind speed were key meteorological drivers; Vegetation, soil moisture content, and slope morphology had relatively limited effects on the spatial distribution of the fire.

Table 1 Results of Variable Importance Analysis

Variable	**Elevation**	**Humidity**	**Wind**	**NDVI**	**Soil Moisture**	**Surface Temperature**	**Aspect**	**Slope**	**Temperature**
Importance	0.452	0.140	0.116	0.073	0.051	0.049	0.040	0.039	0.039

Note: Importance values represent the relative contribution of each variable to wildfire prediction in the Random Forest model

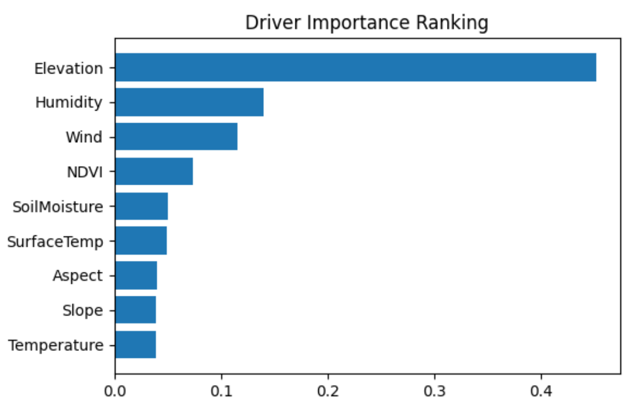

Figure 1 Driver Importance Ranking

5.3 Differences in Environmental Parameters Between Burned and Unburned Areas

To further understand the environmental conditions associated with wildfire occurrence, the average values of key environmental variables were compared between burned and unburned areas. (Table 2) The comparison provides additional insights into the spatial characteristics of wildfire-prone environments during the Marshall Fire.

Burned areas were generally located at higher elevations, with an average elevation of 1,638m compared with 1,582m in unburned areas. Higher-elevation locations along the eastern foothills of the Rocky Mountains are typically characterized by drier atmospheric conditions and greater exposure to downslope wind events. These conditions may contribute to increased wildfire susceptibility.

Table 2 Differences between fire and non-fire areas

Variable	**Non-fire Areas**	**Fire Areas**
NDVI	0.151	0.175
Wind	11.64	10.73
Humidity	0.111	0.088
Elevation	1582	1638
Slope	1.33	1.74

Note: Values indicate the mean environmental conditions observed in burned and unburned areas.

Relative humidity was noticeably lower in burned areas. The average relative humidity within burned pixels was 8.8%, whereas unburned areas exhibited an average value of 11.1%. Lower humidity conditions can accelerate fuel drying and increase vegetation flammability, creating favorable conditions for wildfire ignition and spread.

Burned areas also exhibited slightly steeper terrain. The average slope in burned regions was 1.74°, compared with 1.33° in unburned regions. Although the overall terrain of the study area is relatively gentle, steeper slopes may facilitate fire propagation by enhancing heat transfer and increasing fuel preheating along the upslope direction.

In contrast, the average regional wind speed showed only limited differences between burned and unburned areas. This result may reflect the limitation of daily averaged meteorological datasets, which are unable to fully capture short-duration extreme wind events. Previous reports of the Marshall Fire indicate that localized downslope Chinook winds played a critical role in rapid fire expansion, suggesting that extreme gust events rather than average wind conditions were the dominant wind-related driver.

Overall, the burned areas were characterized by higher elevation, lower relative humidity, and slightly steeper terrain. These environmental characteristics are consistent with the variable importance results obtained from the Random Forest model and further demonstrate the combined influence of topography and meteorological conditions on wildfire occurrence in WUI environments.

5.4 Factor Correlation Characteristics

The correlation coefficient matrix indicates that some meteorological factors are correlated to varying degrees. (Figure 2) Relying on the robustness of the random forest algorithm against multicollinearity, the interference between factors is effectively weakened, and the importance calculation results can objectively reflect the actual contribution of each variable.

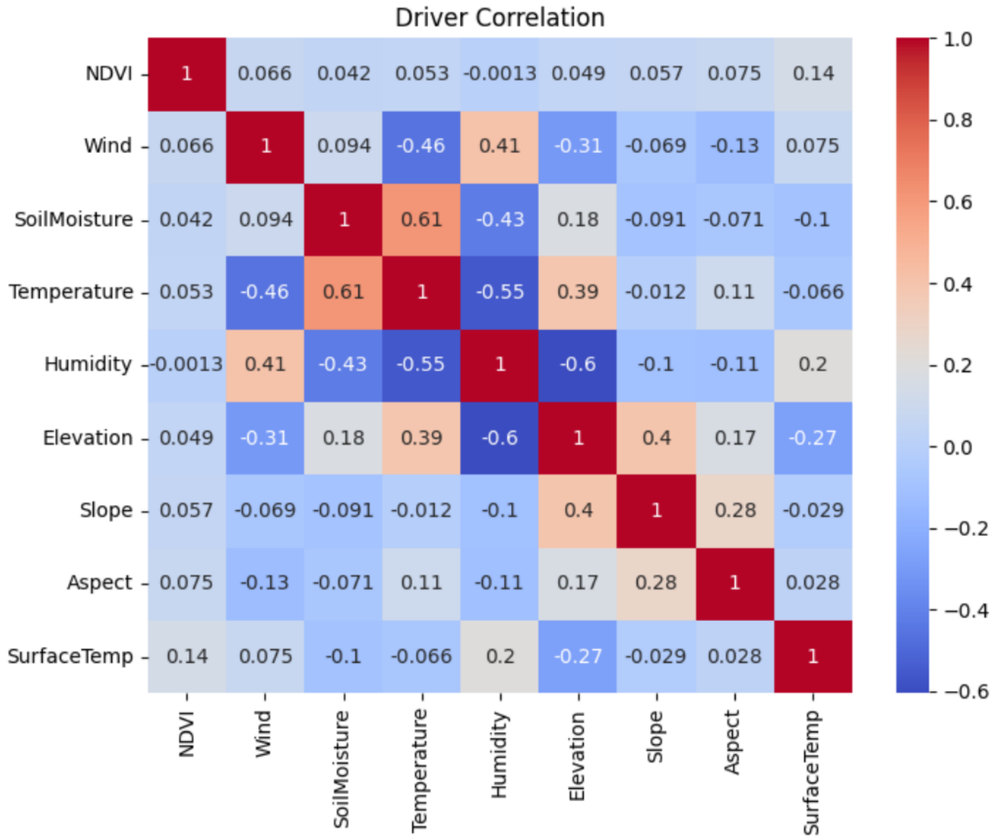

Figure 2 Driver Correlation

5.5 Wildfire Risk Zoning and Risk Reduction Potential

Combined with factor importance weight and spatial raster distribution characteristics of elevation, relative humidity and wind speed, the study area is classified into three risk levels: high-risk zone, medium-risk zone and low-risk zone for differentiated risk reduction layout:

High-risk area: High elevation (>1620 m), slope>1.5°, average relative humidity<9%, consistent with historical burned range, the core priority zone of fire risk reduction; dry shrubs and grassland are densely distributed, fuel removal and real-time meteorological monitoring are the primary reduction paths. The identified high-risk zones represent priority areas for proactive disaster risk reduction interventions. In addition to fuel management, local governments should integrate wildfire risk information into land-use planning and WUI development policies. Restricting further residential expansion within highly exposed foothill areas could significantly reduce future wildfire losses.

Furthermore, installation of automated weather monitoring stations and real-time early-warning systems would improve preparedness during extreme wind events. Community-based evacuation planning and defensible-space regulations should also be strengthened to enhance local resilience. [12]

Medium-risk area: Elevation 1560–1620m, relative humidity9%–12%, transitional zone between mountain and suburb; focus on intermittent fuel thinning and residential surrounding fire isolation belt construction to cut fire spread channel.

Low-risk area: Plain low-elevation region below 1560 m, high humidity and gentle terrain; dominated by daily routine fire publicity and regular vegetation maintenance to control underlying fire risk.

Spatially, high-risk areas concentrate on the eastern foothill valley terrain of Rocky Mountain, which is the key implementation area of fire risk reduction engineering in future.

6 Discussion

Elevation is the primary driving factor, controlled by the local geographical environment of the eastern foothills of the Rocky Mountains: [13] high-altitude areas have lower atmospheric moisture content, a higher proportion of natural xerophytic shrub vegetation, and consistently better combustible dryness compared to low-altitude areas; simultaneously, the mountain slopes are prone to descending hot and dry winds and narrow gusts, and the superposition of these two conditions makes high-altitude areas more prone to fires, matching the spatial distribution pattern of this fire.

Relative humidity and wind speed rank second and third among the driving factors. Low air humidity directly reduces vegetation moisture content, increasing the flammability of combustibles; short-term gusts accelerate air circulation, promoting flame spread, and are the core meteorological triggers for the rapid expansion of the WUI suburban wildfire. [14]

The low importance of NDVI and soil moisture indicates that the spatial distribution of the fire in this case was not dominated by the total amount of surface fuel, but rather by topography and regional dry/wet meteorological conditions.

On the basis of driving mechanism analysis above, differentiated risk reduction should match dominant environmental constraints of different zoning: [15] For high-elevation high-risk regions restricted by terrain and low humidity, passive risk reduction (fuel clearing, isolation belt construction) plus active early warning (valley gust real-time monitoring) should be synchronously deployed; for medium-risk transitional WUI suburbs dominated by meteorological fluctuation, seasonal dry-period vegetation pruning is the main reduction measure; low-risk flat areas adopt daily fire management to control baseline fire risk.

Limitations: The data source is limited to 16-day synthetic NDVI and daily average meteorological data, excluding daily precipitation and wind direction sub-indicators; the analysis only focuses on a single fire. Further analysis could include multiple WUI fires in the same area to optimize the fire risk assessment model. This study only puts forward zoning risk reduction suggestions based on single fire case; multi-case calibration can further optimize quantitative risk reduction efficiency evaluation in follow-up research.

The dominance of elevation identified in this study differs from several previous wildfire studies that reported vegetation condition or fuel moisture as the primary drivers. This discrepancy may be attributed to the unique environmental setting of the Marshall Fire, which occurred within a highly developed WUI under extreme winter wind conditions. In such environments, topographic controls on local microclimate and wind acceleration may become more influential than vegetation abundance alone.

7 Conclusions

The random forest model effectively simulates the Marshall Fire's spatial distribution, achieving an accuracy of 93.7%, and is suitable for quantitative analysis of wildfire driving factors and risk zoning in suburban WUI ecotones.

Topographic elevation is the most critical driving factor in this fire, with an importance of 45.2%; relative humidity and wind speed are key meteorological drivers, and drought together with valley sudden gale significantly raises regional wildfire probability. Burned areas cluster in high-altitude, low-humidity and steep-slope hilly terrain.

According to factor spatial difference, the study divides the research area into high/medium/low three-level fire risk zones and forms hierarchical risk reduction schemes: high-risk mountainous areas prioritize monitoring station construction and fuel removal; medium-risk suburban transition areas build fire isolation zones; low-risk plain areas implement regular daily fire prevention management.

This study quantifies multi-factor driving law of North American WUI wildfire, the risk zoning and matched risk reduction plan can provide technical support for local wildfire risk mitigation and fine prevention management of Colorado similar suburban regions.

The findings demonstrate the value of integrating remote sensing datasets and machine-learning techniques for supporting evidence-based wildfire disaster risk reduction in WUI regions. The proposed framework can be transferred to other fire-prone suburban environments experiencing increasing climate-related wildfire threats.

The study results indicate that when conducting risk management in the WUI area, it is not enough to focus solely on fuel management; topographic exposure must also be incorporated into land use planning, and construction on high-altitude windward slopes should be restricted.

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