Impact of the 2025 California Wildfires on Mountain Lion (*Puma concolor*) Habitat: A Remote Sensing and Species Distribution Modeling Framework

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ABSTRACT

Increasing wildfire frequency and intensity in southern California profoundly impacts ecosystems and keystone species like the mountain lion (*Puma concolor*), which relies on extensive and connected habitats. Quantifying the immediate ecological impact of the January 2025 Los Angeles County wildfires on *Puma concolor* habitat is a critical conservation concern. This study presents a novel, rapid-assessment framework for post-fire habitat evaluation, integrating Sentinel-2 burn metrics and VIIRS anthropogenic proxies via Google Earth Engine (GEE) with MaxEnt species distribution modeling (SDM). Comparative pre- and post-fire habitat suitability models were developed by integrating static environmental variables (topography, bioclimatic) with dynamic indices (Sentinel-2 NDVI, NBR quantifying vegetation response/burn severity; VIIRS nighttime lights quantifying anthropogenic presence) processed in GEE. To isolate the impact of fire-induced environmental changes on habitat suitability, the same set of pre-fire *Puma concolor* occurrence data from GBIF was used for both models. The results reveal a substantial habitat suitability loss of 104.12 km² (54.65%) within fire perimeters, with major losses concentrated in the Palisades, Eaton, and Hughes incidents. Model analysis confirms precipitation patterns (BIO16, BIO18) and temperature seasonality (BIO4) are major habitat drivers, but dynamic factors also played a key role, with post-fire vegetation condition emerging as a critically important factor influencing suitability, highlighting fire's impact on landscape resources. This underscores the necessity of incorporating dynamic, disturbance-specific RS data into SDMs for robust ecological impact assessment and highlights urgent conservation needs for *Puma concolor* in increasingly fire-prone urban-wildland interfaces.

1. INTRODUCTION

Wildfires in Mediterranean climate regions like Southern California have escalated in frequency, intensity, and spatial extent over the past two decades (Alawode et al., 2025; Dorosh et al., 2025), driven by prolonged drought, invasive grasses and extreme Santa Ana wind events (Jennings et al., 2018). The January 2025 Southern California fires (including the Palisades, Eaton, and Hughes Fires) burned over 190 km^2 in Los Angeles County, causing severe human and ecological impacts (California Department of Forestry and Fire Protection, 2025). Beyond the immediate human consequences, such extreme disturbances cause severe ecological damage, removing canopy and vegetation (Li et al., 2022), disrupting soil stability (Pellegrini et al., 2022), altering prey communities and affecting species distributions (Cherry et al., 2018).

Among the species affected by large-scale wildfires, the mountain lion (*Puma concolor*) holds particular ecological significance as an apex predator and a keystone species that plays a critical role in maintaining ecosystem balance (Elbroch & Wittmer, 2012; LaBarge et al., 2022). Mountain lions require expansive and contiguous habitats with sufficient prey availability, and their survival is closely tied to habitat quality and connectivity (Christoff & Devenish-Nelson, 2024; Karandikar et al., 2022; Mbuh & Vruno, 2018). However, wildfires and climate change severely disrupt these conditions by reducing vegetation cover, fragmenting habitats, and threatening prey populations (Jennings et al., 2016). This poses significant challenges to mountain lion persistence in fire-affected landscapes. The purpose of this study is to assess the impact of the 2025 Southern California wildfires on *Puma concolor* distribution.

Species Distribution Models (SDMs) provide a framework for modeling habitat distribution based on environmental covariates and occurrence data, utilized in numerous studies (Guisan et al., 2017; Nunes-Silva et al., 2025; Phillips et al., 2006). MaxEnt, as one of the most widely used SDM models, constructs a probability surface constrained by the principle of maximum entropy, yielding continuous distribution maps that can be thresholded to identify core and marginal habitat (Phillips et al., 2006). As a robust and widely-applied tool, MaxEnt is suitable for modeling the habitat of terrestrial mammals like the mountain lion.

Several studies have employed MaxEnt to model mountain lion (*Puma concolor*) distribution using a range of environmental and anthropogenic variables. Some have focused on topographic, vegetation and hydrological features such as elevation, slope, forest cover, and water availability (Christoff & Devenish-Nelson, 2024; Zeller et al., 2018). Others have emphasized landscape configuration and human disturbance indicators, including road density, edge density and urbanization (Angelieri et al., 2016). In some cases, broader ecological and geographic factors like distances to settlements, protected areas, and bioclimatic variables have also been incorporated (Iranzo et al., 2025).

While these models provide robust predictions, few studies have explicitly incorporated fire as a variable in SDMs. When fire related variables have been included, it is typically represented by more generalized and long-term metrics such as fire frequency or time since the last fire (Swan et al., 2021). In contrast, this study incorporates more detailed pre- and post-fire data, including burn severity and spectral indices, providing a refined

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approach to understanding the impact of fire on species distribution.

Moreover, traditional species distribution models often rely on static environmental variables and limited telemetry datasets, which restrict their capacity to capture large-scale, dynamic shifts in habitat suitability following wildfire events. In contrast, citizen science platforms such as Global Biodiversity Information Facility (GBIF) provide broader spatial and temporal coverage of species occurrence data, enabling more dynamic modeling approaches. By incorporating both relatively stable variables (such as topography) and dynamic factors (such as burn severity and vegetation response), these models can offer more comprehensive insights into species' habitat use. This integrated approach supports adaptive management strategies in the face of increasingly frequent and severe environmental disturbances.

Building upon the value of integrating dynamic and static factors for understanding species habitat use in disturbed landscapes, this study presents a novel framework leveraging remote sensing via Google Earth Engine (GEE) and species distribution modeling (SDM) using MaxEnt in R, alongside geospatial analysis in Python. It develops comparative pre- and post-fire *Puma concolor* habitat suitability models using dynamic indices derived from Sentinel-2 imagery via GEE: the Normalized Burn Ratio (NBR) for burn severity and the Normalized Difference Vegetation Index (NDVI) for vegetation health. These indices are integrated with GBIF occurrences and other anthropogenic and environmental variables to model *Puma concolor* distribution using MaxEnt. This approach accounts for both static (WorldClim bioclimatic, topographic) and dynamic (NBR, NDVI, VIIRS nighttime lights) variables, isolating the impact of wildfires on habitat suitability. This framework provides valuable insights for conservation, aiding in the identification of priority areas for habitat restoration, wildlife corridor planning, and targeted management strategies.

2. METHODS

By combining environmental, anthropogenic and bioclimatic variables with multi-source geospatial data, this study conducted a comprehensive framework for evaluation of wildfire-driven habitat changes. Figure 1 shows the methodology flowchart of the proposed framework.

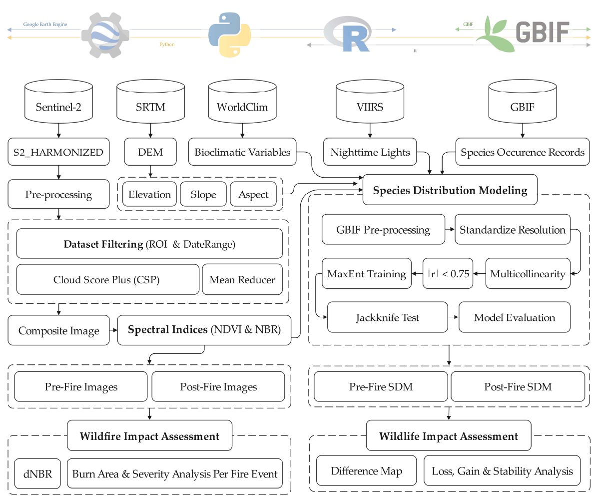

Figure 1. The flowchart of the proposed framework.

2.1 Study Area

The study focuses on Los Angeles County in Southern California, bounded approximately by 33.7°–34.8°N latitude and 117.6°–118.9°W longitude. Elevation ranges from sea level to over 3,000 m, producing steep terrain and diverse microclimates ideal for *Puma concolor* habitat (Bolas et al., 2025; Ernest et al., 2014; Riley et al., 2006). The area is frequently affected by Santa Ana wind events, which can generate gusts exceeding 30m/s, significantly increasing wildfire risk in the wildland–urban interface (Guzman-Morales et al., 2016). Figure 2 demonstrates the study area map along with the January 2025 fire perimeters of L.A. County. Fire perimeters are the result of the "Wildfire Impact Assessment" section of the current study and fire incident names were sourced from CAL FIRE (https://www.fire.ca.gov/incidents/2025/). The Channel Islands were excluded from the study area due to their geographic isolation and the absence of established mountain lion populations. It is important to note that the Kenneth Fire, despite its severity, was not included in this study as it spanned both Los Angeles and Ventura counties, extending beyond the scope of the analysis. All map visualizations are projected in the WGS 84 coordinate reference system (CRS), but quantitative area analysis used WGS 84 / UTM Zone 11 N.

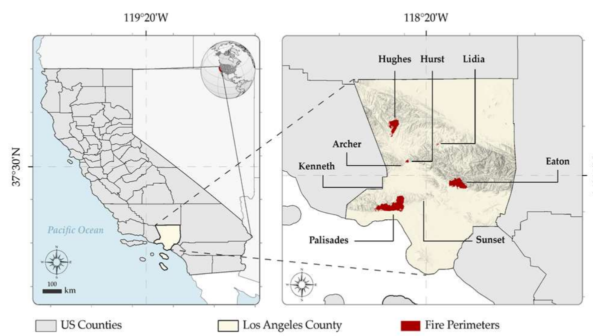

Figure 2. Study area map with January 2025 fire perimeters of Los Angeles County.

2.2 Data Sources

To assess the impact of the 2025 California wildfires on mountain lion (*Puma concolor*) distribution in Los Angeles County, multiple datasets were integrated. These included species occurrence records, topographic variables, remote sensing spectral indices, bioclimatic variables, and an anthropogenic disturbance proxy.

2.2.1 Species Occurrence Data: Presence records of *Puma concolor* were obtained from GBIF (https://www.gbif.org/) using the *pygbif* Python package. This dataset is frequently used in recent studies (Brown & Puschendorf, 2025; Khwarahm, 2025), providing a robust basis for analyzing the species' distribution. GBIF records are compiled from various sources, including iNaturalist, and offer valuable insights into species presence across diverse geographic locations.

2.2.2 Topographic Variables: Topographic variables, including elevation, slope, and aspect, derived from the Shuttle Radar Topography Mission (SRTM) 30-meter digital elevation data. These variables were selected due to their established relevance in modeling *Puma concolor* distribution (Dickson & Beier, 2007).

2.2.3 Remote Sensing Spectral Indices: Remote sensing techniques and spectral indices were used to assess vegetation response and burn severity, both of which influence mountain lion habitat. By leveraging Sentinel-2 imagery and Google Earth Engine (GEE), vegetation productivity and the extent of wildfire impacts are quantified. The NDVI serves as a proxy for prey distribution, such as Mule Deer (*Odocoileus hemionus*), which is the primary prey of *Puma concolor* in California. This, in turn, alters the habitat availability for mountain lions.

2.2.3.1 Vegetation Response: Vegetation response was assessed as a proxy for prey availability (Harvey et al., 2025; Smallidge et al., 2010) using NDVI derived by Sentinel-2 within GEE. The NDVI images were calculated to estimate vegetation productivity and potential prey habitat pre- and post-fire, utilizing the Red (R) and Near-Infrared (NIR) bands of Sentinel-2 satellite imagery. This approach provided insight into how wildfire-driven vegetation shifts may impact mountain lions' habitat.

$$\mathrm{NDVI} = (\rho_{NIR} - \rho_{R}) / (\rho_{NIR} + \rho_{R}) \tag{1}$$

2.2.3.2 Burned Area and Severity: Burn severity analysis was conducted using Sentinel-2 Multispectral Instrument (MSI) imagery within GEE. The NBR was calculated using the Near Infrared (NIR) and Shortwave Infrared (SWIR) bands to assess vegetation condition before and after the fire. The differenced NBR (dNBR) was then derived by subtracting pre-fire NBR values from post-fire NBR values, quantifying and visualizing burn severity (Key & Benson, 2006). Fire perimeters were then delineated based on the dNBR threshold of 0.2.

$$\mathrm{NBR} = (\rho_{NIR} - \rho_{SWIR}) / (\rho_{NIR} + \rho_{SWIR}) \tag{2}$$

$$\mathrm{dNBR} = \mathrm{NBR}_{\text{Pre-Fire}} - \mathrm{NBR}_{\text{Post-Fire}} \tag{3}$$

2.2.4 Bioclimatic Variables: Bioclimatic variables such as annual temperature, precipitation, and seasonality were extracted from WorldClim v1 (~1 km resolution) using Google Earth Engine (Fick & Hijmans, 2017). Table 1 summarizes the bioclimatic variables used in this study.

Code	Variables
BIO1	Annual Mean Temperature
BIO2	Mean Diurnal Range (Max Temp - Min Temp)
BIO3	Isothermality (BIO2/BIO7) ×100
BIO4	Temperature Seasonality (Standard Deviation ×100)
BIO5	Max Temperature of Warmest Month
BIO6	Min Temperature of Coldest Month
BIO7	Temperature Annual Range (BIO5-BIO6)
BIO8	Mean Temperature of Wettest Quarter
BIO9	Mean Temperature of Driest Quarter
BIO10	Mean Temperature of Warmest Quarter
BIO11	Mean Temperature of Coldest Quarter
BIO12	Annual Precipitation
BIO13	Precipitation of Wettest Month
BIO14	Precipitation of Driest Month
BIO15	Precipitation Seasonality (Coefficient of Variation)
BIO16	Precipitation of Wettest Quarter
BIO17	Precipitation of Driest Quarter
BIO18	Precipitation of Warmest Quarter
BIO19	Precipitation of Coldest Quarter

Table 1. Bioclimatic Variables of WorldClim.

2.2.5 Anthropogenic Disturbances: To account for anthropogenic influences on *Puma concolor* SDMs, nighttime light data from the Visible Infrared Imaging Radiometer Suite (VIIRS) was integrated via GEE. VIIRS captures artificial illumination originating from urban areas, infrastructure, and other human activities, providing a continuous and pixel-level measure of anthropogenic presence (Ma, 2018). This dataset is widely recognized in previous research (Escobar et al., 2015; Zheng et al., 2023) as an indicator of urbanization, population density, and development intensity, providing valuable insight into the potential effects of light pollution and human disturbance on species distributions.

2.3 Data Preprocessing

To ensure analytical consistency and address spatial data quality, all environmental predictors underwent rigorous preprocessing. Full metadata for all employed data, including their source (as detailed in Section 2.2), native spatial/temporal resolution, and processing levels, were considered. All raster layers were harmonized for analysis: they were resampled to a uniform 500 m spatial resolution using bilinear interpolation and precisely aligned by reprojecting them to a single projection system and datum: WGS 84 / UTM Zone 11 N (EPSG: 32611). This common coordinate reference system ensures spatial co-registration and allows for accurate area calculations (e.g., habitat loss in km²). For the dynamic remote sensing data, specific quality controls were implemented. Sentinel-2 data (S2_HARMONIZED, Level-1C) was processed in GEE, where the Cloud Score Plus (CSP) algorithm (threshold 0.60) was applied to mask cloud-contaminated pixels, ensuring high thematic fidelity of the derived indices. Mean composite images were then generated for pre- and post-fire timeframes to reduce sensor-specific noise.

A comprehensive spatial data quality assessment was conducted on the *Puma concolor* occurrence data from GBIF, as this represents the most significant source of potential spatial error. First, records were filtered to retain only those within California and meeting a strict geometric accuracy threshold (*coordinateUncertaintyInMeters* < 1000 m), explicitly excluding points with high locational uncertainty. To mitigate spatial sampling bias and spatial autocorrelation, which can inflate model performance, a spatial thinning procedure was applied using the *spThin* package in R (Aiello-Lammens et al., 2015). A 5 km thinning distance with 50 replicates was used, and the replicate retaining the maximum number of points was selected for modeling. This process ensures that the input occurrence data is of the highest available quality and spatial independence. Finally, to isolate the impact of fire, the thinned dataset was temporally filtered (pre-fire: September 7, 2024 – January 7, 2025; post-fire: January 7, 2025 – May 7, 2025), and predictor values were extracted using bilinear interpolation. To address statistical quality, all predictors were tested for multicollinearity (Pearson's $|r| > 0.75$), and redundant bioclimatic variables were excluded to ensure model interpretability and stability.

2.4 Species Distribution Model

Species distribution modeling was conducted using MaxEnt, a machine learning-based approach grounded in Maximum Entropy theory (Phillips et al., 2006). MaxEnt is widely applied in species distribution modeling (Fardone et al., 2025; Huang et al., 2024) due to its ability to model species distributions using presence-only data, without requiring explicit absence records. This method estimates the most uniform probability distribution subject to constraints derived from environmental variables at observed occurrence locations (Phillips et al., 2006).

For both pre- and post-fire MaxEnt models, the same GBIF-derived species occurrence dataset was used. While using separate datasets for each time period is also common in spatiotemporal studies, this approach was avoided to isolate the direct impact of the wildfires. By using the same points for both models, it was ensured that the differences in predicted habitat suitability were driven by actual changes in the environment resulting from the wildfire, rather than inconsistencies in the species presence data. This method also reduced spatial and temporal sampling biases, allowing for a clearer interpretation of the wildfire's ecological effects. In contrast to projections used in climate change impact assessment studies, this analysis relied on real observed environmental layers that reflect the actual conditions post-fire, making it more directly applicable to understanding habitat changes. Tests using temporally distinct datasets introduced additional complexities, such as shifts in other environmental factors that went beyond the scope of this study (which focused specifically on the effects of the wildfire). Therefore, using a consistent dataset provided a more controlled and accurate assessment of the ecological impact of the fire.

It should be noted that while the SDMs were developed at the regional scale of California to capture broad environmental variation, subsequent analyses were focused on Los Angeles County. This regional focus ensured ecological relevance, aligned with the spatial extent of the fire events and minimized the risk of overfitting by reducing the potential bias from uneven sampling across the state.

2.4.1 MaxEnt Model Configuration: Proper configuration of MaxEnt model settings is vital to ensure reliable and unbiased predictions in species distribution modeling (Feng et al., 2019; Phillips et al., 2006; Senay et al., 2013). Pre- and post-fire SDMs were developed using *MaxEnt v3.4.1* via the *dismo* R package. Presence data were clipped to the California state boundary using GBIF occurrence records. To generate background data (pseudo-absences), a uniform grid of 10,000 points was created across California using GEE's *coveringGrid* function. The centroids of these grid cells served as background points, ensuring uniform spatial coverage and minimizing bias. Raster values for all environmental variables were sampled at these locations using the same interpolation method. Model features were restricted to linear, quadratic, product and hinge (LQHP) types and the regularization multiplier was set to 1. Models were trained using ten-fold cross-validation, with a maximum of 1,000 iterations or convergence threshold of 0.00001. The logistic output format was selected and extrapolation was enabled to support predictions beyond training conditions.

2.4.2 Performance Evaluation and Variable Importance: Model performance was evaluated using the Area Under the Curve (AUC) from the Receiver Operating Characteristic (ROC) curve, the True Skill Statistic (TSS) (Allouche et al., 2006; Liu et al., 2016), and the Continuous Boyce Index (CBI) (Boyce et al., 2002). AUC values range from 0.5 (random prediction) to 1.0 (perfect prediction), with TSS accounting for both sensitivity and specificity, offering a comprehensive measure of model accuracy. The CBI was used to assess prediction consistency across continuous suitability values. A threshold-independent distribution map was generated to visualize the species' predicted habitat. Variable importance was determined using the Jackknife test, which evaluates the change in model performance when each variable is excluded.

3. RESULTS AND DISCUSSION

This section presents a comprehensive analysis of the impact of the January 2025 wildfires on *Puma concolor* habitats in Los Angeles County. The results are organized into three key areas: (1) an assessment of fire impact and burn severity based on Sentinel-2 imagery (Section 3.1), (2) a detailed evaluation of changes in species distribution pre- and post-fire (Section 3.2), and (3) a performance evaluation of the MaxEnt species distribution model, including an analysis of the most influential environmental variables (Section 3.3).

3.1 Wildfire Impact Assessment

The analysis of fire impact for the seven wildfires in Los Angeles County used Sentinel-2 imagery. The burn severity was derived using the dNBR method based on spectral changes in the imagery, which were then classified into the common standard burn severity classes (unburned, low severity, moderate low severity, moderate high severity and high severity). To extract fire perimeters, an initial approximated bounding box was manually delineated around each fire to facilitate identification and labeling. Subsequently, binary thresholding with a dNBR threshold value of 0.2 was applied to delineate burned areas from unburned regions, effectively isolating fire-impacted zones. This approach allowed for the extraction of burned area in km². Table 2 summarizes the burned area (BA) in km^2, burn severity percentages (HS: High-Severity, LS: Low-Severity and MS: Moderate-Severity), and mean and maximum values of dNBR for each January 2025 L.A. County fire event.

Fire	BA (km^2)	LS	MS	HS	Max $_{dNBR}$	Mean $_{dNBR}$
Palisades	101.71	20.7	25.8	53.4	1.15	0.37
Eaton	52.50	28.1	30.4	41.4	1.17	0.34
Hughes	39.70	46.1	41.7	12.1	0.81	0.22
Hurst	2.66	59.7	35.3	4.8	0.68	0.14
Lidia	0.94	75.2	11.8	12.9	0.86	0.09
Sunset	0.13	62.0	34.6	3.3	0.58	0.01
Archer	0.06	77.8	19.6	2.5	0.60	0.02

Table 2. Summary of burned area and burn severity for the January 2025 wildfires in Los Angeles County.

The results show significant variability in burn severity across the fires, with high-severity burns ranging from 2.5% (Archer) to 53.4% (Palisades). The overall burned areas ranged from 0.06 km² (Archer) to 101.71 km² (Palisades). Together, they burned over 197.7 km² of land (≃1.6% of the total land area of Los Angeles County). Furthermore, Figure 3 shows the pre- and post-fire NDVI and NBR maps along with the raw and classified dNBR maps of Los Angeles County, California.

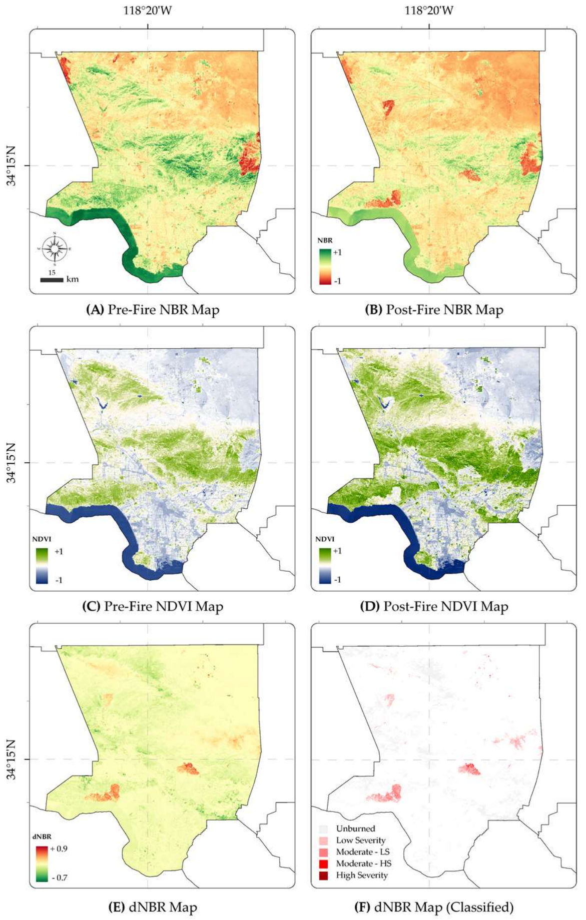

Figure 3. Pre-fire (A) and post-fire (B) NBR maps, pre-fire (C) and post-fire (D) NDVI maps, (E) dNBR map and (F) classified dNBR map of Los Angeles County.

3.2 Wildlife Impact Assessment

To evaluate the impact of the January 2025 wildfires on *Puma concolor* habitat suitability, two SDMs incorporating static and dynamic environmental variables were generated for both (A) pre- and (B) post-fire conditions (Figure 4).

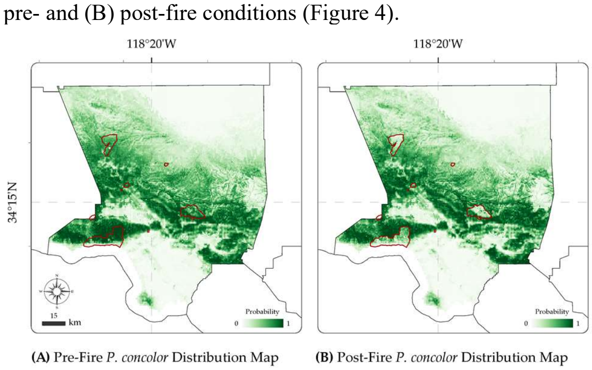

Figure 4. (A) Pre-fire and (B) post-fire predicted distribution maps of *Puma concolor* in Los Angeles County, California.

To quantify spatial changes in habitat suitability, a pixel-wise subtraction was performed between the post-fire and pre-fire SDMs, resulting in a continuous difference map (ΔSDM) that highlights areas of habitat gain or loss following the wildfires.

For clearer interpretation, the ΔSDM was reclassified into five categories: strong loss ($\Delta \leq -0.4$), moderate loss ($-0.4 < \Delta \leq 0.1$), stable ($-0.1 < \Delta < +0.1$), moderate gain ($+0.1 \leq \Delta < +0.4$) and strong gain ($\Delta \geq +0.4$). Figure 5 displays the resulting difference map (A) and its classified version (B).

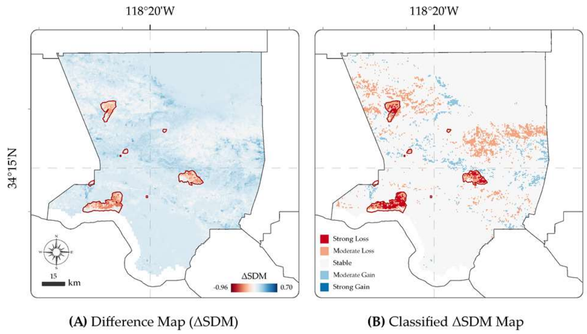

Figure 5. Change in *Puma concolor* predicted distribution following the January 2025 L.A. wildfires: (A) Continuous difference map (ΔSDM) and (B) Classified difference map.

To further quantify the ecological impact of the wildfires, changes in high-suitability habitat area were calculated for each fire event. High habitat suitability was defined using a fixed threshold of 0.5 applied to the SDM outputs. While multiple wildfires occurred during the study period, some were too small in size to be accurately captured at the 500 m spatial resolution of the SDMs (which were based on a 10 m resolution for wildfire impact assessment). Additionally, certain fires occurred in urban areas or regions that did not overlap significantly with *Puma concolor* habitats. Therefore, these fires were excluded from the wildlife impact analysis and were only considered in the wildfire impact assessment, which focuses on the overall burn severity and affected area.

The total high habitat areas (in km^2) for both the pre-fire and post-fire conditions, along with the calculated habitat loss in km^2 and percentages are presented in Table 3. The total high habitat area before the fires was 190.51 km^2, which decreased to 86.39 km^2 post-fire, reflecting a substantial habitat loss of 104.12 km^2, or 54.65%. Among the individual fire events, the Palisades Fire resulted in the greatest absolute loss of high-suitability habitat, with 44.49 km^2 affected. The Eaton and Hughes fires followed, with habitat losses of 30.89 km^2 and 27.71 km^2, respectively. The Hurst Fire, although smaller in extent, still caused a reduction of 1.03 km^2. These losses reflect the significant impact of the 2025 wildfires on mountain lion habitats, with some fires affecting more than half of the pre-fire high-suitability areas.

Fire	Pre-fire High Habitat (km^2)	Post-fire High Habitat (km^2)	Habitat Loss (km^2)	Habitat Loss (%)
Palisades	89.64	45.15	44.49	49.63
Eaton	59.74	28.85	30.89	51.70
Hughes	38.14	10.42	27.71	72.66
Hurst	2.99	1.97	1.03	34.04
TOTAL	190.51	86.39	104.12	54.65

Table 3. Pre- and post-fire estimates of high-suitability habitat area (km^2) for *Puma concolor* across major 2025 wildfires in Los Angeles County, Southern California.

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3.3 MaxEnt Model Performance

Model performance was assessed using ten-fold cross-validation across both pre-fire and post-fire MaxEnt models. The evaluation metrics included the TSS, AUC-ROC, and the CBI. Each metric was computed per fold and summarized using mean, standard deviation (SD) and range values. TSS was calculated by identifying the threshold that maximized the sum of sensitivity and specificity (MaxSSS). AUC-ROC provided a threshold-independent measure of discrimination ability. The CBI, based on Spearman's correlation between predicted suitability and presence frequency across binned predictions, measured model calibration and ecological relevance. Results indicated strong and consistent performance for both time periods. The mean TSS was 0.642 before the fires and 0.647 after. AUC-ROC values were similarly high, with averages of 0.888 (pre-fire) and 0.891 (post-fire), signifying excellent discriminatory power. CBI scores further supported the models' reliability, with means of 0.916 and 0.930, respectively. These results demonstrate that the models consistently captured patterns of suitable habitat across cross-validation folds.

Metric	Statistic	Pre-Fire	Post-Fire
TSS	*Mean*	0.642	0.647
	SD	0.011	0.019
	Range	0.627-0.655	0.63-0.678
AUC-ROC	*Mean*	0.888	0.891
	SD	0.006	0.003
	Range	0.882-0.894	0.885-0.894
CBI	*Mean*	0.916	0.930
	SD	0.045	0.030
	Range	0.85-0.947	0.894-0.969

Table 4. MaxEnt model evaluation metrics for pre-fire and post-fire periods.

3.4 Jackknife Analysis

Figure 6 presents the Jackknife analysis of regularized training gain for pre-fire and post-fire MaxEnt models, using the same pre-fire presence data but environmental layers reflecting the impact of the 2025 fires in L.A. County. The overall model fit improved slightly post-fire (gain of 1.0425 vs. 1.0095 pre-fire). In the pre-fire model, BIO4 (temperature seasonality) showed the highest standalone gain (0.4848), with BIO16 (0.4026) having the second highest. NDVI also showed notable standalone predictive power (0.2302). In the post-fire model, BIO4's standalone gain remained high (0.4848), while NDVI's decreased (0.1919) and NBR's increased notably (0.2097), indicating the growing isolated importance of fire-related vegetation metrics.

Omission tests (Gain Without) revealed key variables contributing unique information. In both periods, removing BIO16 (Precipitation Wettest Quarter) caused the largest drop in gain, highlighting its consistent primary importance regardless of fire. BIO4 and BIO18 (Precipitation Warmest Quarter) also showed substantial drops when removed, indicating their ongoing relevance. Importantly, the unique contribution of NBR increased substantially post-fire (a larger drop in gain when removed compared to pre-fire), reflecting the critical role of burn severity and vegetation recovery in shaping post-fire habitat. The interpretable patterns observed in the corresponding variable response curves also validate these findings. These results demonstrate that while climate variables are fundamental drivers, fire disturbance significantly amplifies the importance of burn-specific vegetation condition (NBR) in determining post-fire puma habitat dynamics.

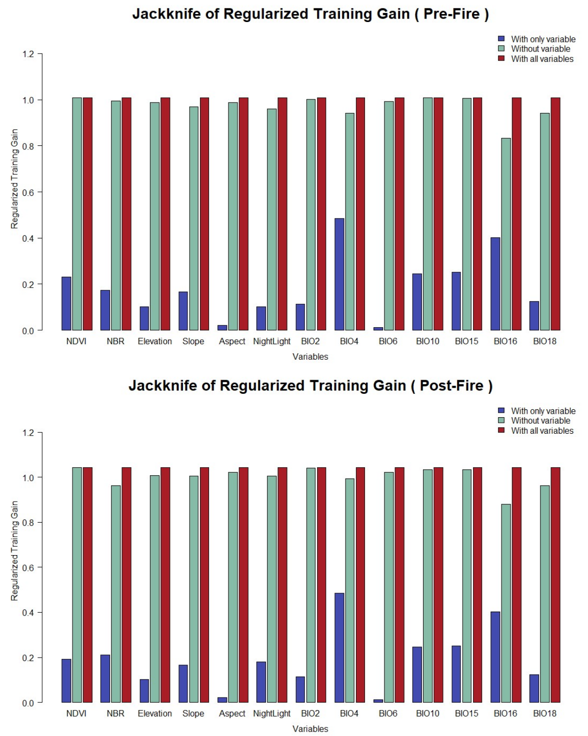

Figure 6. Jackknife of regularized training gain for pre-fire and post-fire MaxEnt models.

4. CONCLUSION

This study's primary contribution is a novel, rapid-assessment framework for post-fire ecological impact, integrating Sentinel-2 burn severity indices and VIIRS anthropogenic proxies via Google Earth Engine (GEE) with MaxEnt SDMs. The analysis provides a comprehensive assessment of the January 2025 wildfires' impacts on mountain lion (*Puma concolor*) habitats in Los Angeles County. The findings highlight the significant changes in habitat suitability for *Puma concolor*, with substantial losses in high-suitability habitats following the fires. The analysis revealed that the wildfires resulted in a considerable reduction in suitable habitats for mountain lions, with an overall loss of 54.65% of high-suitability habitat across the affected regions. These losses were most noticeable in larger fires, such as the Palisades, Eaton and Hughes fires, which respectively accounted for up to 44.49, 30.89 and 27.71 km^2 of habitat loss. Despite the severity of the wildfires, certain areas exhibited moderate habitat gains, suggesting potential opportunities for recovery in some regions, particularly where vegetation was less impacted by the fire. Through species distribution modeling, this study identified key environmental factors influencing *Puma concolor* habitat suitability. Variables related to precipitation patterns (BIO16, BIO18) and temperature seasonality (BIO4) emerged as consistently important drivers across both pre- and post-fire periods. Furthermore, post-fire analysis highlighted the increased critical role of vegetation burn severity and recovery (NBR) in shaping habitat suitability, reflecting the fire's impact on landscape resources. These insights into core habitat requirements and dynamic post-fire responses are essential for guiding future conservation efforts and wildlife management strategies in fire-prone landscapes. The robustness of the applied species distribution models, demonstrated by high AUC-ROC, TSS, and CBI values, highlighted the reliability of the proposed approach in assessing the ecological impacts of wildfires. The integration of multi-source and multi-scale data (ranging from Sentinel-2 imagery to bioclimatic and anthropogenic factors) provided a detailed view of the wildfire's ecological consequences, offering valuable insights for managing habitat protection and restoration efforts. In conclusion, the 2025 Southern California wildfires have significantly impacted *Puma concolor* habitat in Los Angeles County, necessitating adaptive management strategies to support mountain lion recovery. Future research should focus on long-term monitoring of fire-impacted habitats, explore post-fire recovery processes, and evaluate the effectiveness of habitat restoration initiatives. Given the increasing frequency of regional wildfires, these findings underscore the urgent need for proactive conservation strategies to mitigate the impact of fire on vital apex predators.

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