Wildfire Risk Prediction and Assessment in Los Angeles and Ventura Counties, California

Stanley Osondu., Nicholas Aboagye

School of Economic, Political and Policy Sciences, University of Texas at Dallas

DOI: https://dx.doi.org/10.47772/IJRISS.2025.908000231

Received: 22 July 2025; Accepted: 07 August 2025; Published: 05 September 2025

ABSTRACT

Wildfires represent a critical hazard in Southern California, threatening life, infrastructure, and ecosystems. This study integrates diverse geospatial datasets like historic fire perimeters, topography, climate, soil, and building footprints to assess wildfire risk in Los Angeles and Ventura Counties. Using ArcGIS Pro, a weighted overlay analysis was implemented, where environmental factors such as vegetation, slope, aspect, and climate were normalized and assigned weights based on expert judgment. The final risk map classified the study area into low, moderate, and high-risk zones. Results reveal that approximately 25.1% of buildings fall within high-risk areas, 54.2% in moderate-risk zones, and 20.7% in low-risk areas, highlighting significant exposure of built infrastructure. Model validation using historical fire perimeters achieved 78.96% accuracy, with a kappa coefficient of 0.43, confirming reasonable predictive reliability. These findings underscore the urgent need for targeted mitigation strategies, such as restricting urban development in high-risk corridors, enhancing defensible space standards, and updating building codes. The approach provides a replicable GIS-based framework for integrating environmental and exposure data into wildfire planning, offering actionable insights for emergency managers, land-use planners, and policymakers to improve community resilience under increasing wildfire threats.

Keywords: Wildfire Risk assessment, Wildfire prediction, Spatial Analysis, Remote Sensing

INTRODUCTION

Wildfire events in California have grown in frequency and severity, fueled by prolonged droughts, rising temperatures, and land-use patterns that increase human presence in fire-prone regions. According to Cal Fire (2023), Los Angeles and Ventura Counties have experienced several high-impact wildfires over the past decade, resulting in loss of lives, property, and biodiversity. This trend aligns with findings by Syphard et al. (2019), who emphasized that climate variability and human expansion into wildland–urban interface zones are primary drivers of wildfire incidence in Southern California. Similarly, Radeloff et al. (2018) highlight the expanding footprint of development in fire-prone landscapes, increasing exposure and complicating emergency management.

This study aims to assess wildfire risk across a portion of Los Angeles and Ventura Counties using an integrated geospatial approach. It combines environmental, topographic, and anthropogenic variables to model risk levels and identify exposed buildings. The methodology builds on a multi-criteria decision-making framework within a GIS environment, providing both spatially explicit risk maps and quantifiable exposure estimates.

LITERATURE REVIEW

Wildfire risk modeling typically incorporates environmental variables such as vegetation (fuel load), topography, and climatic factors. Chuvieco et al. (2010) emphasized the critical role of fuel continuity and moisture content, while slope and aspect influence fire behavior by affecting wind speed, heat transfer, and solar radiation exposure (Miller & Ager, 2013).

Recent studies have explored machine learning (ML)-based wildfire prediction models, such as Random Forest, MaxEnt, and Support Vector Machines, which leverage nonlinear relationships between variables to produce highly accurate risk maps (Parisien et al., 2019; Jain et al., 2020). While these methods can outperform traditional approaches in predictive precision, they require large, high-quality training datasets and advanced computational resources, making them less accessible for resource-constrained agencies. In contrast, weighted overlay methods, as employed in this study, offer transparency, simplicity, and ease of implementation within GIS platforms like ArcGIS Pro. This makes them suitable for local and regional planning where interpretability and replicability are priorities. Moreover, in the context of Southern California, climate change is expected to exacerbate wildfire risk by increasing the frequency of droughts, heatwaves, and extreme wind events (Westerling, 2016). Therefore, models that can be regularly updated using publicly available geospatial datasets remain crucial for adaptive risk management.

Incorporating historical fire perimeters has proven effective in validating predictive models (Alcasena et al., 2018), while weighted overlay methods have been widely used to combine multiple raster inputs based on their relative contribution to fire risk (Kalogirou et al., 2020). These models can be enhanced by integrating infrastructure data, which captures human exposure and vulnerability. Zhu et al. (2020) showed that building-level analysis provides a more nuanced understanding of community risk, particularly in wildland–urban interface zones.

This study draws upon these methods, adding the dimension of exposure quantification using high-resolution OpenStreetMap building data, which is spatially joined with predicted risk classes to identify the number of structures at risk.

METHODOLOGY

Study Area

The study area spans wildfire-prone regions of Los Angeles and Ventura Counties in Southern California. The terrain is marked by coastal mountains, vegetation, and expanding suburban developments. Both counties are historically vulnerable to large wildfires, as evidenced by events like the Woolsey and Thomas Fires. For the sake of transparency and integrity, Generative AI was used in this research for idea exploration and language improvement.

Data Sources

Table 1. Dataset and their respective sources

Dataset	Source
Historic Fire Perimeters	Los Angeles County Enterprise GIS Portal (EGIS LA County)
DEM (elevation, slope, aspect)	USGS (Ventura and Los Angeles Counties)
County Boundary	California Open Data Portal (https://data.ca.gov)
Climate Data (temperature, precipitation)	USDA PRISM (https://datagateway.nrcs.usda.gov)
Soil Raster	NRCS SSURGO, U.S. Department of Agriculture
Building Footprints	OpenStreetMap (via Geofabrik API)

Processing and Risk Modeling

- **Topography**: DEMs were used to derive slope and aspect layers in ArcGIS Pro. The weight assignment for the weighted overlay analysis was based on expert judgment informed by prior studies and domain knowledge of wildfire behavior in Southern California. Higher weights were allocated to variables with strong influence on fire spread, such as vegetation/fuel load and land use/land cover (25% each), due to their direct role in determining combustible material availability. Topographic factors like slope and aspect (10% each) were given moderate importance because they influence fire intensity and direction. Elevation and distance to structures were weighted at 10% each, reflecting their contribution to exposure and risk amplification. Climatic variables mean annual temperature and precipitation were

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue VIII August 2025

weighted lower (5% each) as their effects are indirect but still relevant in shaping fuel moisture and ignition potential. These weights align with standard practices in wildfire risk modeling while accommodating regional characteristics identified through expert consultation.

- **Climate**: Mean annual temperature and precipitation from PRISM were reclassified based on dryness and heat conditions conducive to fire spread.
- **Soil**: SSURGO soil raster was classified based on organic matter and water retention capacity.
- **Historic Fires**: Fire perimeters were overlaid with the modeled risk zones to visually assess model accuracy.
- **Weighted Overlay**: All factors were normalized to a 1–5 scale and combined using weights derived from literature and personal judgment (LULC: 25%, Fuel load: 25%, slope: 10%, aspect: 10%, DEM: 10%, distance to buildings: 10%, annual precipitation: 5%, mean temperature: 5%).
- **Exposure Analysis**: OpenStreetMap building polygons were spatially joined to the wildfire risk map. Using "Summarize Within" and "Zonal Statistics," the number of buildings in each risk class (low, moderate, high) was computed.

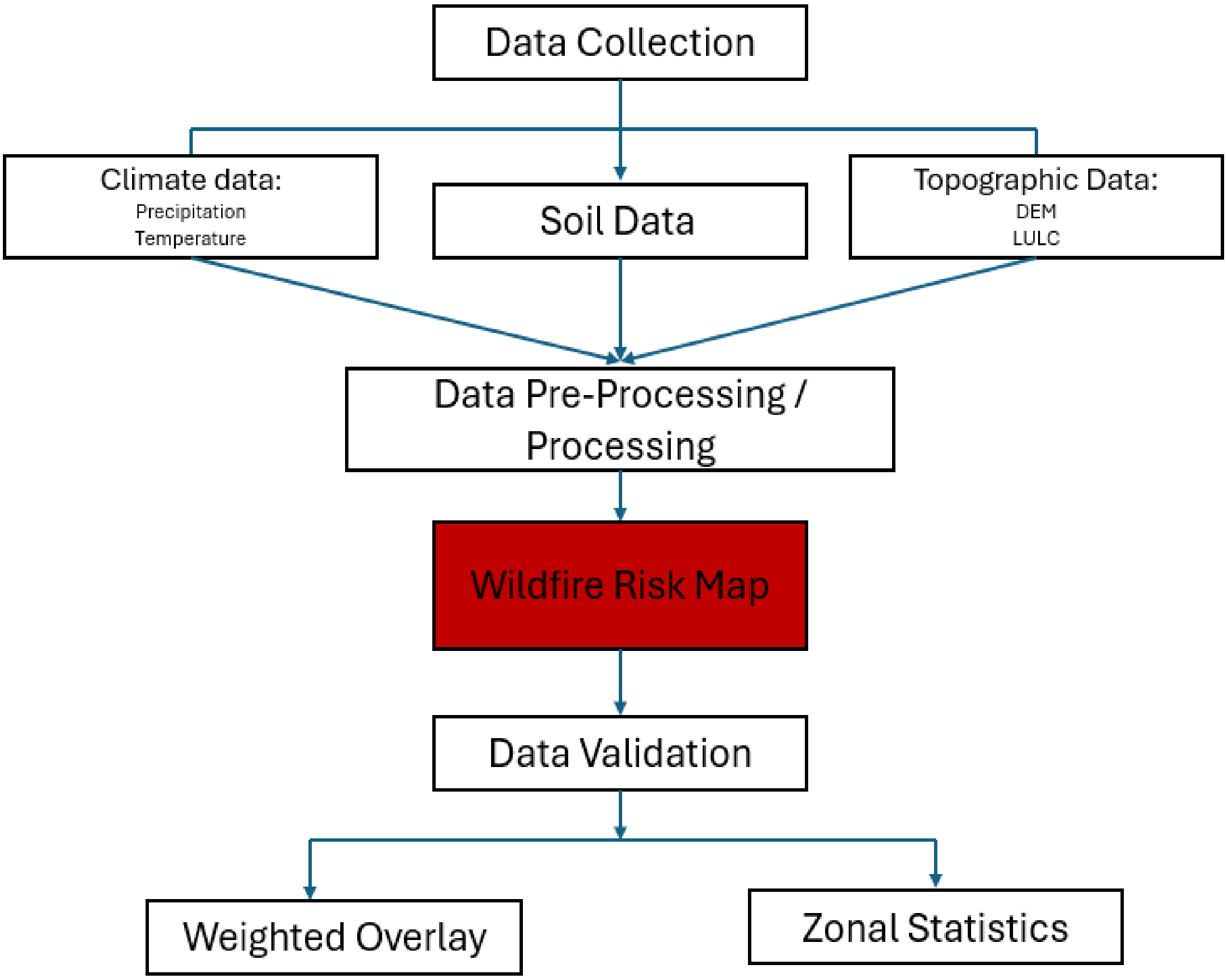

Figure 1. Project process and workflow.

Post-Classification and Exposure Analysis

After generating the wildfire risk map via weighted overlay, the output raster was converted to vector polygons for spatial analysis. These polygons were spatially joined with building footprint data from OpenStreetMap using the "Summarize Within" and "Zonal Statistics" tools in ArcGIS Pro. This enabled quantification of the number of buildings situated within each wildfire risk category (low, moderate, and high). The overlay of building data provides a detailed understanding of structural exposure, which serves as a proxy for community vulnerability.

RESULTS AND DISCUSSION

Wildfire Risk Classification

A wildfire risk map was generated using weighted overlay analysis in ArcGIS Pro, classifying the study area into three categories: low, moderate, and high risk. After converting the raster risk map into vector polygons, a spatial join was performed with OpenStreetMap building footprints to assess structural exposure across the risk zones.

Building Exposure in Wildfire Risk Zones

The spatial join and zonal summary revealed a total of 397,302 buildings within the wildfire risk zones across the study area. The building counts per wildfire risk category are summarized as follows:

Table 2. Number of buildings within each wildfire risk category.

Risk Class	Gridcode	Number of Buildings
Low Risk	1	82,249
Moderate Risk	2	215,342
High Risk	3	99,711

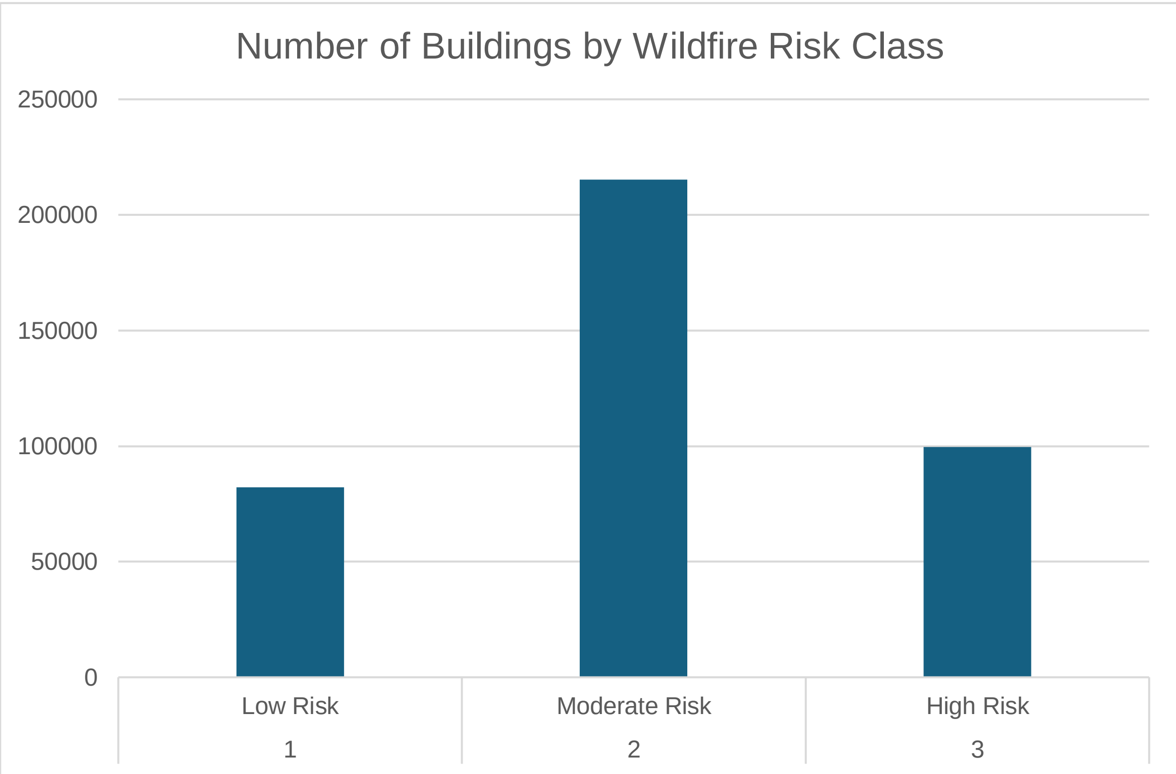

Figure 2. Bar chart showing the number of buildings in each wildfire risk class.

These results indicate that over half (54.2%) of the exposed buildings fall within the moderate-risk zones, while a significant 25.1% are in high-risk zones. Only 20.7% of the buildings are situated in areas classified as low wildfire risk.

Risk Map Validation with Historic Fire Perimeters

The combined map showing wildfire risk overlaid with historic fire perimeters from Los Angeles County revealed a strong spatial correspondence. Many of the regions historically affected by wildfires particularly in the mountainous and wildland–urban interface areas are currently classified as high or moderate risk, reinforcing the validity of the model outputs.

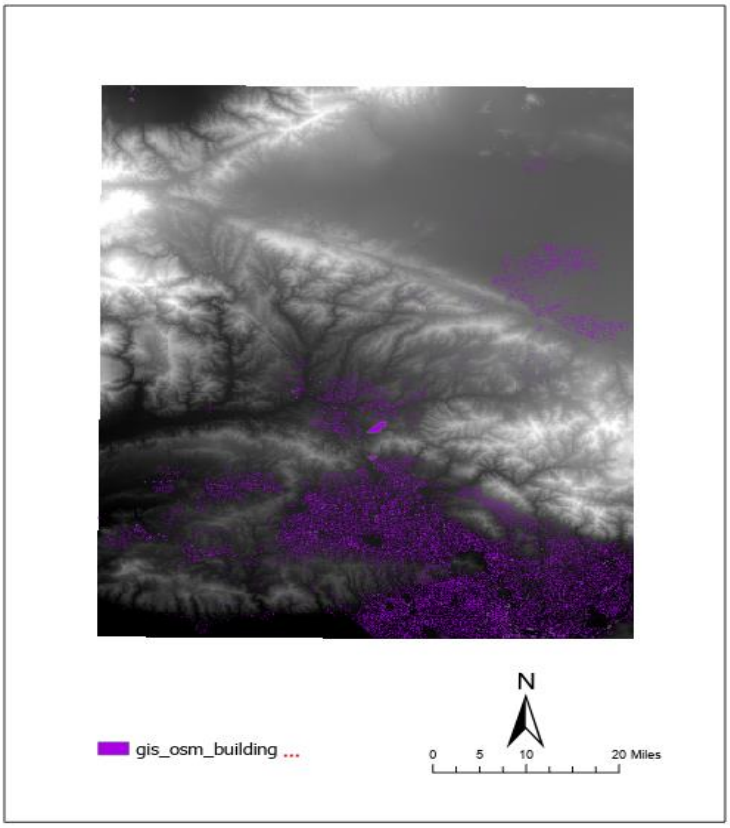

Figure 3. DEM with OpenStreetMap building footprints in Los Angeles and Ventura Counties.

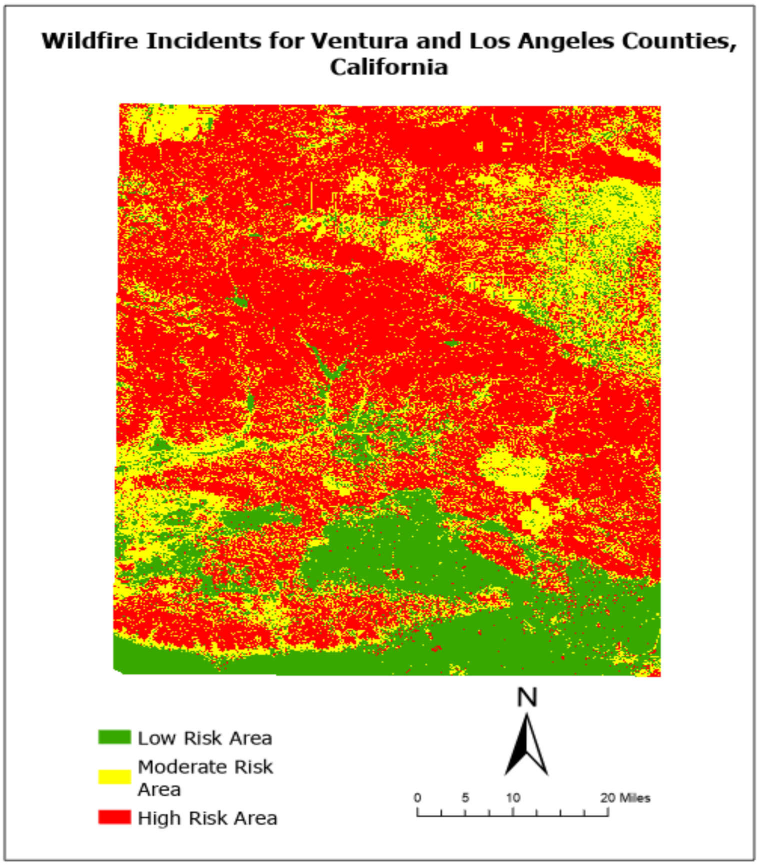

Figure 4. Classified wildfire risk zones: low, moderate, and high

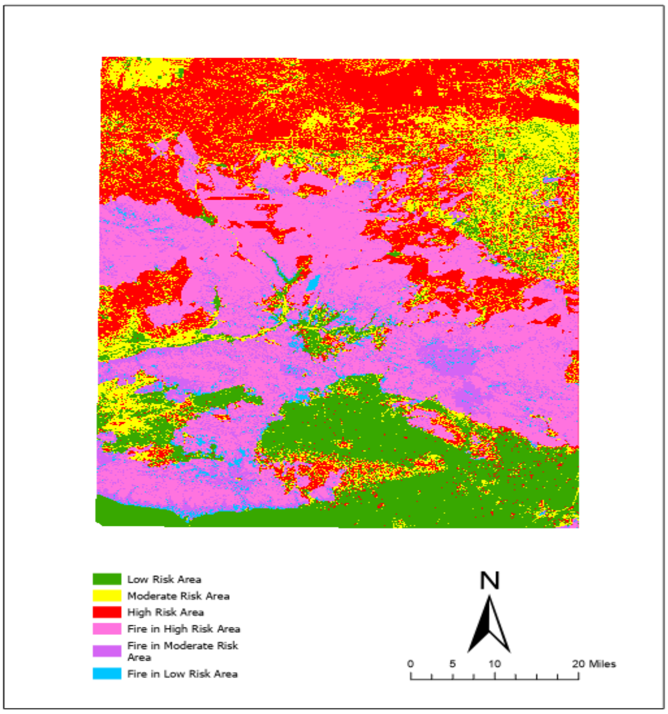

Figure 5. Historic fire perimeters overlaid on wildfire risk map

Model Validation

To evaluate the accuracy of the wildfire risk prediction model, a comparison was conducted between the generated risk map and historical fire perimeter data. Using a confusion matrix approach, each cell in the study area was assigned a class based on the predicted wildfire risk and whether it had been historically burned. This yielded values for true positives (TP), false positives (FP), false negatives (FN), and true negatives (TN), allowing for the calculation of key model performance metrics.

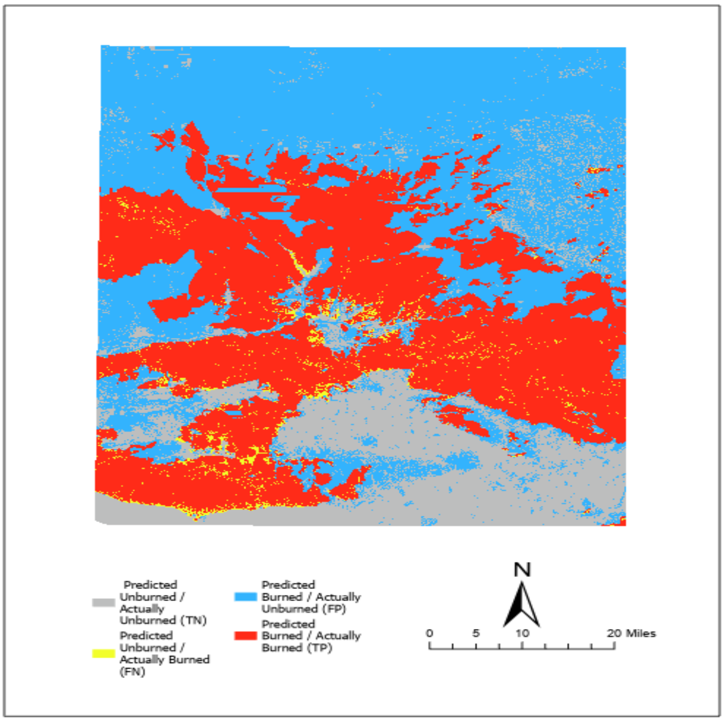

Figure 6. Confusion Matrix using Historic Risk Maps and Wildfire Risk Maps

Table 3. Confusion Matrix of Predicted vs Actual Fire Occurrence.

Predicted \ Actual	Burned	Unburned	Total
Burned	TP = 419,049,123.19	FP = 460,332,401.94	879,381,525.13
Unburned	FN = 196,259,824.68	TN = 2,034,200,965.57	2,230,460,790.25
Total	615,308,947.87	2,494,533,367.52	3,109,842,315.39

Table 4. Model performance metrics derived from confusion matrix.

Metric	Value
Accuracy	78.96%
Precision	47.68%
Recall	68.11%
Kappa	0.43

DISCUSSION

Comparison to Similar Studies

Urban expansion into wildland-urban interface (WUI) zones is a key driver of wildfire risk in Southern California. Radeloff et al. (2018) reported that the WUI in the U.S. grew by 33% between 1990 and 2010, with California experiencing some of the most rapid development in high-risk zones. This trend has amplified structural exposure, as reflected in this study's finding of nearly 100,000 buildings located in high-risk areas across Los Angeles and Ventura Counties. Compared to similar analyses, such as Syphard et al. (2019), which identified approximately 22% of structures in high-risk zones across broader Southern California, the proportion in this study (25.1%) underscores the localized severity of exposure in these counties. This concentration of development near chaparral-dominated landscapes, combined with increasing climatic variability, suggests that land-use planning policies must evolve to curb expansion in fire-prone regions and implement stricter building regulations to mitigate losses.

The methodology and findings of this study are consistent with prior work in wildfire risk assessment. Alcasena et al. (2018) demonstrated the utility of integrating environmental, topographic, and human exposure variables in wildfire modeling, similar to this study’s approach using weighted overlay and building footprint data. Kalogirou et al. (2020) also emphasized the effectiveness of GIS-based multi-criteria analysis in identifying risk-prone regions, particularly in Mediterranean and chaparral environments that resemble California’s terrain. Unlike these studies, however, the current research adds building-level exposure analysis using OpenStreetMap data, offering finer-scale insights into infrastructure vulnerability.

Implications for Policy and Planning

The study provides actionable insights for land use planners, emergency managers, and local governments. The quantified exposure of over 397,000 buildings, including nearly 100,000 in high-risk areas, highlights the urgency of updating building codes and enforcing defensible space regulations. These results can support zoning laws that restrict expansion into high-risk areas and guide investments in wildfire resilience, such as community fire breaks and evacuation planning. The validated risk model could also be integrated into local GIS platforms for use in real-time response systems.

Limitations and Future Directions

Several limitations affect the generalizability of the results. First, the building footprint data from OpenStreetMap may not fully reflect recent construction, especially in peri-urban areas. Second, the model is static and does not account for dynamic variables such as wind direction, fuel moisture, or real-time vegetation conditions. Third, historic fire perimeters, while useful for validation, may not capture future ignition patterns influenced by climate change. Future research should consider machine learning approaches, such as Random

Forest, to enhance model precision. Additionally, incorporating satellite-based vegetation indices and temporal fire occurrence data could improve both prediction accuracy and real-time applicability.

CONCLUSION

The wildfire risk model demonstrates that a significant portion of built infrastructure in Los Angeles and Ventura Counties remains vulnerable to future wildfire events. With nearly 100,000 buildings located in high-risk zones, the findings underscore the urgency of implementing defensible space standards, zoning regulations, and emergency evacuation planning in these regions.

The high concentration of exposed structures in moderate-risk areas (over 215,000 buildings) also suggests that mitigation should not be limited to extreme-risk zones. These areas, often located adjacent to high-risk terrain or with less severe but still fire-prone characteristics, could become dangerous under the influence of changing climate conditions or fire suppression gaps.

The close spatial overlap between high-risk zones and historic burn scars highlights the persistent nature of wildfire threats in certain corridors, including the Santa Monica Mountains, Topanga Canyon, and regions near Simi Valley and Agoura Hills. These results are consistent with earlier studies by Alcasena et al. (2018) and Syphard et al. (2007), which emphasized recurring ignition zones and the role of terrain and land use in fire behavior.

From a methodological standpoint, the integration of building-level exposure analysis distinguishes this study from broader landscape-based models. While previous research has focused on environmental conditions alone, the addition of OpenStreetMap data provides a more community-centric risk model, making it directly actionable for planners and local agencies.

However, limitations exist in the spatial resolution and completeness of building data, particularly in sparsely populated zones. Additionally, while historic fire perimeters serve as a good proxy for model validation, they do not necessarily predict future ignitions, especially with evolving urban footprints and climate dynamics.

Overall, this study reinforces the value of combining geospatial environmental modeling with infrastructure exposure assessment to generate practical, risk-informed outputs for wildfire management and planning.

RECOMMENDATIONS

The findings of this study underscore the urgent need for proactive wildfire mitigation strategies in Los Angeles and Ventura Counties. Given the significant number of structures particularly nearly 100,000 buildings located in high-risk zones, land use planning should prioritize restricting future developments in these vulnerable areas. Zoning regulations must be revised to reflect updated risk assessments, discouraging expansion into zones with recurring fire histories or proximity to steep, vegetation-rich terrain.

Equally important is the consistent enforcement of defensible space standards, which require property owners to manage vegetation and reduce fuel loads near buildings. These measures are especially crucial in moderate- and high-risk zones where structural density increases the likelihood of fire spread and damage. Integrating the validated wildfire risk model into county-level GIS platforms could further support emergency preparedness by enabling real-time visualization of risk zones, informing evacuation routes, and assisting in the placement of fire breaks or suppression resources.

Retrofitting efforts such as installing fire-resistant materials and upgrading community infrastructure should be prioritized in high-density areas that fall within the elevated risk zones. Regions such as Topanga Canyon, the Santa Monica Mountains, and Simi Valley stand out as strategic targets for such interventions due to their persistent exposure and fire history. Finally, the study recommends greater investment in up-to-date, high-resolution spatial data, especially building footprints, to enhance the accuracy of exposure analysis and better inform both policy decisions and academic modeling in future research.

REFERENCES

1. Alcasena, F. J., Ager, A. A., Bailey, J. D., & Pineda, N. (2018). Towards a comprehensive wildfire risk assessment framework for the United States: Integrating fuel, topography, weather, and values. *Forest Ecology and Management*, 432, 99–113. https://doi.org/10.1016/j.foreco.2018.08.014
2. Chuvieco, E., Aguado, I., Yebra, M., Nieto, H., Salas, J., & Martín, M. P. (2010). Development of a framework for fire risk assessment using remote sensing and geographic information system technologies. *Ecological Modelling*, 221(1), 46–58. https://doi.org/10.1016/j.ecolmodel.2008.11.017
3. Kalogirou, S., Mytilinou, V., & Mavrakis, A. (2020). Wildfire risk mapping using GIS and multi-criteria decision analysis: A case study from Cyprus. *Natural Hazards*, 104, 2065–2088. https://doi.org/10.1007/s11069-020-04239-9
4. Miller, C., & Ager, A. A. (2013). A review of recent advances in risk analysis for wildfire management. *International Journal of Wildland Fire*, 22(1), 1–14. https://doi.org/10.1071/WF11114
5. Syphard, A. D., Radeloff, V. C., Hawbaker, T. J., & Stewart, S. I. (2007). Human influence on California fire regimes. *Ecological Applications*, 17(5), 1388–1402. https://doi.org/10.1890/06-1128.1
6. Syphard, A. D., Rustigian-Romsos, H., Mann, M., Conlisk, E., & Moritz, M. A. (2019). The relative influence of climate and housing development on current and projected future fire patterns and structure loss across three California landscapes. *Global Environmental Change, 56*, 41–55. https://doi.org/10.1016/j.gloenvcha.2019.03.007
7. Radeloff, V. C., Helmers, D. P., Kramer, H. A., Mockrin, M. H., Alexandre, P. M., Bar-Massada, A., ... & Stewart, S. I. (2018). Rapid growth of the US wildland–urban interface raises wildfire risk. *Proceedings of the National Academy of Sciences, 115*(13), 3314–3319. https://doi.org/10.1073/pnas.1718850115
8. Zhu, Z., Xian, G., Homer, C., & Meyer, D. (2020). Mapping wildland–urban interface in the United States: A national dataset. *Remote Sensing of Environment*, 246, 111807. https://doi.org/10.1016/j.rse.2020.111807
9. Cal Fire (2023). Top 20 Most Destructive California Wildfires. California Department of Forestry and Fire Protection. Retrieved from https://www.fire.ca.gov