

Development of an Explainable GeoAI Wildfire Risk Analysis Model Using Multi-Source Geospatial Data

Esra Günaydın^{1*}, Muhammed Oğuzhan Mete¹, Furkan Ali Küçük^{2,3}, Ayça Hafizoğlu¹, Mahmut Oğuz Selbesoğlu^{1,4}

¹ ITU, Department of Geomatics Engineering, 34469, Istanbul, Türkiye - esgunaydin, metemu, hafizoglu21, selbesoglu@itu.edu.tr

² ITU, Graduate School, Atmospheric Sciences Program, 34469, Istanbul, Türkiye - kucukfur@itu.edu.tr

³ TUBITAK Polar Research Institute, Kocaeli, Türkiye - furkan.kucuk@tubitak.gov.tr

⁴ ITU, Polar Research Center, Istanbul, Türkiye

Keywords: Wildfire, Hazard, Vulnerability, Risk Analysis, GeoAI

Abstract

Accounting for approximately 31% of the global land surface, forests play a critical and indispensable role in sustaining ecological balance. Among the various pressures affecting forests, forest fires constitute a major environmental problem, posing significant threats to natural ecosystems while disrupting forestry activities and leading to substantial economic losses. In Türkiye, forest fires are predominantly observed in the Aegean, Mediterranean, and Marmara regions. This study presents a proactive, explainable GeoAI framework for wildfire risk analysis by integrating multi-source geospatial data. The methodology calculates a physical hazard index by evaluating advanced ensemble machine learning algorithm, specifically extreme gradient boosting (XGBoost) with the latter demonstrating superior predictive performance. The model is driven by topographic, meteorological, biotic and anthropogenic parameters. In parallel, a comprehensive vulnerability matrix encompassing physical, social, economic and environmental dimensions is constructed utilizing the Best-Worst Method (BWM). These two main components are spatially synthesized in a Geographic Information Systems (GIS) environment. The model's interpretability is enhanced focusing on feature importance to identify the primary drivers of fire ignition and spread. Results demonstrate that anthropogenic pressures and Wildland-Urban Interface (WUI) dynamics are the most significant risk determinants. The resulting high-resolution maps provide a robust Spatial Decision Support System (SDSS) for local authorities, enabling targeted mitigation strategies and contributing to the development of sustainable, smart and resilient cities.

1. INTRODUCTION

Global climate change, escalating anthropogenic pressures and unprecedented rates of unplanned urbanization have fundamentally altered the scale and frequency of natural disasters worldwide. In the face of these prolonged climatic anomalies and expanding human footprints, traditional reactive disaster management which primarily focuses on suppression and post-crisis response has proven structurally insufficient to protect modern populations. Consequently, the paradigm of Sustainable, Smart and Resilient Cities (SSC/SRC) has emerged as a central pillar of contemporary urban planning (Khan et al., 2023). This framework necessitates a fundamental shift towards a proactive, preparedness-oriented model driven by advanced spatial technologies and big data analytics. Within this context, forest fires represent one of the most critical environmental challenges of the 21st century they are no longer confined to isolated rural landscapes but are increasingly encroaching upon urban perimeters. Such events pose severe threats to the ecological balance, permanently disrupt forestry activities and trigger catastrophic socio-economic losses on a regional scale.

The Marmara Region of Türkiye exemplifies this escalating and multifaceted threat. It serves as a strategic geopolitical and socio-economic hub, characterized by exceptionally dense demographic structures, intricate regional transportation networks and maximum industrial capacity (Arda et al., 2025). The region's highly heterogeneous land cover and the continuous, uncontrolled expansion of Wildland-Urban Interface (WUI) zones create a volatile spatial dynamic. In these transitional WUI areas, residential settlements, commercial facilities and critical industrial zones are deeply and dangerously intertwined with highly flammable forest boundaries (O'Connor et al., 2016). As a result, wildfires in the

Marmara Region transcend purely ecological destruction and rapidly evolve into cascading systemic crises (Pourghasemi et al. 2023). A paramount concern in such industrialized landscapes is the potential for Natech (Natural Hazard Triggering Technological Disasters) events. If a wildfire breaches industrial sectors or chemical storage zones, it can precipitate secondary technological disasters, infrastructural collapse and massive supply chain disruptions, thereby directly threatening urban life safety, energy transmission grids and drinking water basin security.

To construct a robust, proactive defense mechanism against these systemic threats, modern disaster risk reduction (DRR) strategies must leverage the integration of Geographic Information Systems (GIS), Remote Sensing (RS), and Artificial Intelligence (AI). Historically, spatial fire hazard assessments relied heavily on traditional statistical models or purely expert-judgment-based Multi-Criteria Decision Making (MCDM) methods (Arda et al., 2025; Uthappa et al., 2025). However, these conventional approaches often fail to accurately capture the highly complex, non-linear relationships among dynamically interacting topographic, meteorological, biotic and anthropogenic variables (Tonbul 2024). The advent of GeoAI and cloud-based geospatial platforms has revolutionized this domain by enabling the rapid, near-real-time processing of massive, multi-source satellite imagery to continuously monitor fuel load dynamics, meteorological indices and vegetation stress. Concurrently, advanced machine learning (ML) algorithms specifically ensemble learning architectures like Random Forest (RF) and eXtreme Gradient Boosting (XGBoost) have demonstrated superior analytical performance, effectively navigating spatial data heterogeneity and maximizing predictive accuracy for fire ignition probabilities

(Eskandari et al. 2020; Shi and Zhang 2023; Zerouali et al., 2025).

Despite their high predictive power, advanced ML algorithms are frequently criticized for their black-box nature, which obscures the underlying mathematical decision-making mechanics and limits their operational adoption by local policymakers (Tonbul 2024; Tonbul and Veraverbeke 2026). To bridge this gap, the integration of Explainable AI (XAI) is critical. Utilizing techniques such as SHapley Additive exPlanations (SHAP), researchers can decode complex ML models, providing transparent feature importance rankings that reveal precisely how and why each spatial criterion contributes to regional fire risk (Tonbul 2024; Uthappa et al. 2025). Furthermore, a holistic disaster model must recognize that physical hazard is only one half of the risk equation. To determine true urban exposure, physical hazards must be spatially intersected with multidimensional vulnerability. To quantify this vulnerability, the Best-Worst Method (BWM) offers a mathematically optimized alternative to traditional MCDM methods, significantly reducing inconsistency and cognitive load while establishing a robust hierarchy of physical, social, economic and environmental vulnerabilities (Arda et al., 2025; Batur et al., 2025; Vujović et al., 2025).

The primary objective of this study is to develop a comprehensive, explainable GeoAI wildfire risk analysis framework for the Marmara Region utilizing multi-source geospatial data. The proposed methodology uniquely integrates a physical hazard model, developed by evaluating XGBoost algorithm with a multidimensional vulnerability matrix quantified via BWM. By employing feature importance analysis, the study aims to interpret the primary socio-ecological drivers of wildfire risk, ensuring that the predictive outputs are transparent and highly actionable. Ultimately, this integrated approach seeks to deliver a highly reliable Spatial Decision Support System (SDSS) that empowers local governments to formulate targeted mitigation policies, establish critical ecological buffer zones and advance the long-term resilience of sustainable and smart cities.

2. STUDY AREA

The Marmara Region, located in northwestern Türkiye and encompassing a total area of approximately 67,000 km², serves as a critical geopolitical, economic and demographic bridge connecting the continents of Asia and Europe. Beyond its geographical centrality, the hazard profile of this territory is shaped by a highly complex, tripartite interplay of climatic, topographic, biotic and anthropogenic factors, making it an exceptionally volatile environment for wildfire propagation (Özcan et al., 2025; Sivrikaya and Demirel 2025). The geographic location and administrative boundaries of the Marmara Region was given in Figure 1.

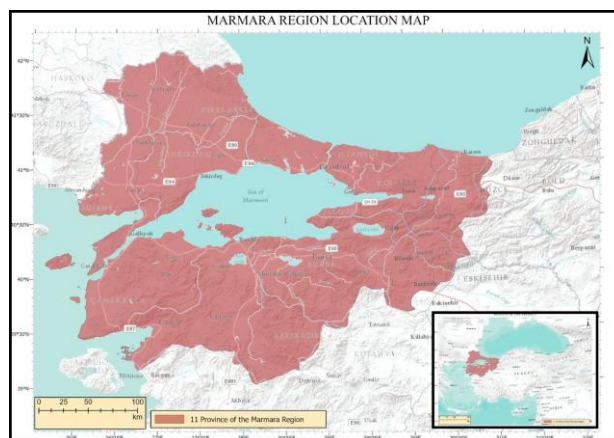


Figure 1. Geographic location and administrative boundaries of the Marmara Region, highlighting the complex climatic and topographic transition zones.

Climatologically, the Marmara Region functions as a unique macro-climatic transition zone where the Black Sea, Mediterranean and Continental climate systems intersect. The southern and western peripheries of the region, notably encompassing provinces such as Çanakkale and Balıkesir, exhibit prominent Mediterranean climate characteristics. These areas are subjected to prolonged summer droughts, low relative humidity and high-temperature anomalies, which drastically reduce the moisture content of live and dead fuels (Tonbul 2024; Tonbul and Veraverbeke 2026). These severe climatic conditions are further exacerbated by the dense spatial distribution of highly flammable coniferous tree species, particularly the Turkish Red Pine, which dominates the southern biotic belt and pushes the regional ignition threshold to critical levels. Furthermore, the region's complex geomorphology characterized by rugged topographic barriers such as the Kaz Mountains, Samanlı Mountains and Mount Uludağ creates natural wind corridors and steep slope dynamics. These topographical features act as physical catalysts, significantly accelerating upward convective heat transfer and the overall rate of fire spread (Sivrikaya and Demirel 2025; Yılmaz et al., 2021).

Figure 2 indicates the number of forest fires belonging to the five provinces with the highest wildfire statistics in the Marmara Region over a 20-year period (2004-2024) (GDF, n.d.). The forest fire inventory for the Marmara Region was obtained retrospectively from the General Directorate of Forestry for the period between 2015 and 2025.

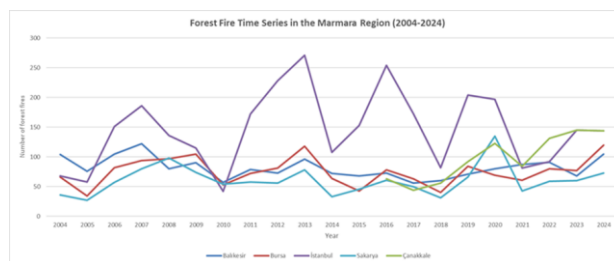


Figure 2. Forest Fire Time Series for the Five Provinces with the Highest Wildfire Statistics in the Marmara Region

Beyond its physical and ecological vulnerabilities, the Marmara Region stands as Türkiye's undisputed industrial and demographic epicenter, hosting over 30% of the national population (Arda et al., 2025). The continuous, rapid expansion

of urban settlements, coupled with dense highway networks and sprawling industrial facilities, has catalyzed the formation of highly complex WUI zones. In these increasingly fragmented landscapes, the boundaries between the built environment and natural forest ecosystems are profoundly blurred. The direct spatial intertwining of industrial production sites, logistics hubs and residential areas with combustible forest fuels generates massive anthropogenic pressure (Eskandari et al., 2020; Tonbul and Veraverbeke 2026). This intense human mobility and infrastructural footprint make the region exceptionally susceptible to human-induced fire ignitions, effectively transforming rural ecological hazards into complex urban security crises (Khan et al., 2023; Uthappa et al., 2025).

The severity of this threat is empirically supported by historical statistical records, which demonstrate that over a ten-year examination period (2015-2024), the Marmara Region experienced a total of 1,489 forest fires. Although it ranks sixth nationally in terms of overall fire occurrence, the region's extraordinary population density, strategic economic infrastructure and intense human activity designate it as a critical proactive risk reduction hotspot, where the socio-economic and systemic impacts of wildfires are uniquely devastating. Finally, to ensure the highest degree of metric precision and to minimize geometric and areal distortions during the micro-level spatial modeling of these complex dynamics.

3. METHODOLOGY

This study's methodological architecture is based on a multi-tiered geospatial data-processing pipeline that integrates GeoAI-based predictive hazard classification with multi-criteria spatial vulnerability assessments to develop a holistic wildfire risk and exposure model (Figure 3).

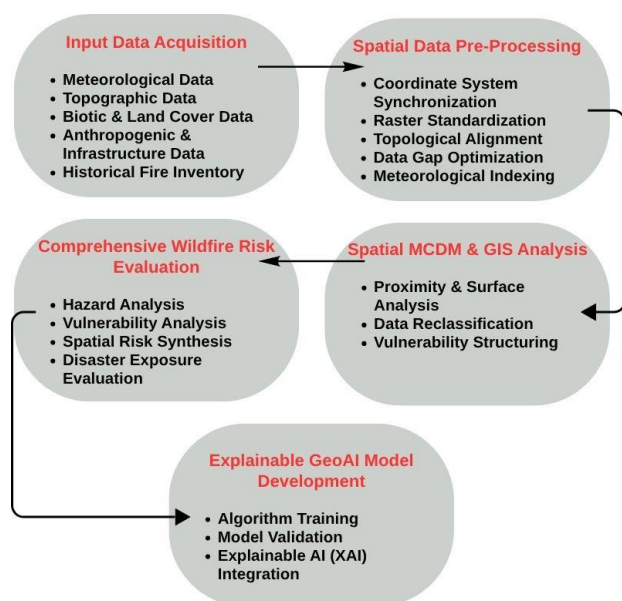


Figure 3. Comprehensive methodological flowchart illustrating the integration of GeoAI hazard modeling and BWM vulnerability assessment

3.1 Data Acquisition and Preprocessing

A highly heterogeneous dataset was constructed by aggregating high-resolution satellite imagery, meteorological reanalysis datasets and global vector inventories. Topographic variables dictating physical fire behavior specifically slope, aspect and

elevation were derived directly from the NASA SRTM 30m Digital Elevation Model (DEM). Meteorological parameters acting as dynamic fire triggers, including temperature, relative humidity, precipitation, wind speed and wind direction, were acquired from the ERA5-Land monthly averaged dataset. Simultaneously, vegetation health, fuel load distribution and biotic characteristics were monitored utilizing Sentinel-2 MSI (Level-2A) imagery and Copernicus Global Land Service products. Anthropogenic ignition sources and pressure metrics, such as distance to road networks, structural settlements and power transmission lines, were extracted from OpenStreetMap (OSM) and the Global Human Settlement Layer (GHS-BUILT/POP). The specifications of the dataset are given in Table 1. Data marked with an asterisk (*) in the spatial resolution column of Table 1 are provided in vector format and therefore do not have an inherent spatial resolution.

To ensure absolute analytical integrity and prevent topological deviations during spatial overlay operations, a strict spatial synchronization protocol was rigorously applied. All disparate datasets were mathematically reprojected to the EPSG:5637 (TUREF/TM30) coordinate reference system, which minimizes areal and linear metric distortions across the Marmara Region and were resampled to a standardized 30x30 m spatial resolution. During resolution standardization, categorical datasets (e.g., tree types, land cover) were resampled using the Nearest Neighbor algorithm to preserve discrete class boundaries without data corruption, whereas continuous physical surfaces (e.g., temperature, DEM) utilized Bilinear Interpolation to maintain smooth radiometric gradients. Topological mismatches and microscopic cell misalignments were entirely eliminated by enforcing a Snap Raster rule, utilizing the 30m DEM as the absolute spatial baseline to guarantee 100% cell-to-cell overlap. Furthermore, an expanded Bounding Box processing extent strategy was deployed to prevent statistical interpolation errors and edge effects at the region's borders.

A critical data recovery protocol was also implemented to address spatial gaps in the coarse-resolution (11.6 km) ERA5-Land meteorological data along the region's complex coastal morphologies. These horizontal NoData gaps, which occur when coarse meteorological pixels fall over the sea surface rather than the indented coastlines, were computationally resolved utilizing the Euclidean Allocation algorithm (Arda et al. 2025; Kazemi et al., 2025). This approach propagated valid terrestrial meteorological values into coastal forest pixels up to a 15 km search radius and was seamlessly integrated via Raster Algebra conditional statements to ensure unbroken spatial continuity across the land-sea interface.

Data	Data Source	Spatial Resolution
Slope	USGS EarthExplorer (NASA SRTM 1 Arc-Second Global)	30m
Aspect	USGS EarthExplorer (NASA SRTM 1 Arc-Second Global)	30m
Elevation	USGS EarthExplorer (NASA SRTM 1 Arc-Second Global)	30m
TWI (Topographic Wetness Index)	Raster Calculator Formula via DEM	30m
Temperature	"ERA5-Land Monthly Averaged (ECMWF/Copernicus) (Resample: Bilinear)"	11634.5m
Relative Humidity	"ERA5-Land Monthly Averaged (ECMWF/Copernicus) (Resample: Bilinear)"	11634.5m
Wind Speed	"ERA5-Land Monthly Averaged (ECMWF/Copernicus) (Resample: Bilinear)"	11634.5m
Wind Direction	"ERA5-Land Monthly Averaged (ECMWF/Copernicus) (Resample: Bilinear)"	11634.5m
Precipitation	"ERA5-Land Monthly Averaged (ECMWF/Copernicus) (Resample: Bilinear)"	11634.5m
Lightning	"ERA5-Land Monthly Averaged (ECMWF/Copernicus) (Resample: Bilinear)"	11634.5m
Solar Radiation	"NASA SRTM 1 Arc-Second Global (Derived via ArcGIS Area Solar Radiation Tool via DEM)"	30m
Drought Index	TerraClimate (via GEE)	4km
Canopy Cover	Copernicus Global Land Service (TCD - Tree Cover Density)	10m
Tree Type	Copernicus High Resolution Layer (FTY - Forest Type)	10m
NDVI	Sentinel-2 MSI (Level-2A)	10m
NBR	Sentinel-2 MSI (Level-2A)	10m
Distance to Roads	OpenStreetMap (OSM)	*
Distance to Settlements	GHS-BUILT-S (Global Human Settlement Layer)	100m
Distance to Agricultural Areas	Esri 10-Meter Land Cover	10m
Distance to Power Lines	OpenStreetMap (OSM)	*
Population Density	Global Human Settlement Layer (GHS)-POP	100m
Fire Intensity	General Directorate of Forestry	*
Fire Recurrence Rate	General Directorate of Forestry	*

Table 1. Inventory of multi-source geospatial datasets, including raw spatial resolutions and derivation sources.

3.2 GeoAI-Based Hazard Modeling

The hazard component of the framework quantitatively isolates the physical probability of fire ignition and subsequent propagation. Historical forest fire records spanning a ten-year period (2015-2025) were acquired from the General Directorate of Forestry (OGM) and utilized to generate precise fire and non-fire spatial target samples, thereby constructing a statistically balanced dataset required for robust machine learning. Daily atmospheric volatility and climatic stressors were integrated into the algorithm by utilizing key meteorological and climatological indices, specifically temperature, relative humidity, solar radiation, the Palmer Drought Severity Index (PDSI) and Convective Available Potential Energy (CAPE) lightning metrics.

Probability-based wildfire hazard prediction models were trained utilizing XGBoost algorithm. This advanced ensemble tree-based methodology were specifically selected for its superior capacity to process multidimensional datasets, manage spatial heterogeneity and accurately model the complex, non-linear relationships among interacting meteorological, topographic, biotic and anthropogenic variables without overfitting (Eskandari et al., 2020; Tonbul 2024). The XGBoost model utilizes iterative gradient boosting to effectively minimize residual errors and maximize predictive accuracy for rare ignition events. Model performance was rigorously evaluated using overall accuracy, f-1 score, recall, precision.

3.3 Spatial Vulnerability Assessment

While hazard models strictly assess the physical and thermodynamic probability of a fire, the vulnerability dimension measures the potential socio-economic, ecological and infrastructural devastation that occurs upon exposure (Kazemi Veisari et al., 2025; Özcan et al., 2025). The comprehensive vulnerability framework was meticulously structured across five fundamental dimensions containing 19 distinct spatial factors: Physical (e.g., critical infrastructure facilities, distance to power lines, WUI proximity), Social (e.g., population density, education, income, elderly ratio), Economic (e.g., tourism and cultural heritage areas), Environmental (e.g., protected areas, endemic biodiversity, drinking water basins) and Accessibility/Response Capacity (e.g., distance to fire stations, road connectivity, slope barriers).

To eliminate the inconsistencies and computational inefficiencies inherent in traditional hierarchical weighting methods such as the Analytical Hierarchy Process (AHP), which would demand an impractical 171 pairwise comparisons for 19 criteria the BWM was proactively employed. BWM structurally optimizes multi-criteria decision making by requiring only 35 pairwise comparisons based on strategically selected Best-to-Others and Others-to-Worst reference vectors. This mathematical optimization significantly reduces cognitive load and data input errors, ensuring a much lower Consistency Ratio (CR) and calculating highly exact impact coefficients for each vulnerability factor (Arda et al., 2025; Vujović et al., 2025).

To synthesize this array of heterogeneous spatial data (spanning units of meters, degrees, Celsius and percentages), all continuous and categorical vulnerability layers were reclassified into a standardized 1 (Very Low) to 5 (Very High) scoring scale (Uthappa et al., 2025). The Natural Breaks (Jenks) algorithm was predominantly utilized for continuous statistical distributions (e.g., distance gradients and vegetation indices) to

identify natural variance jumps, whereas Manual Intervals were strictly enforced for parameters governed by universal physical thresholds (e.g., specific slope angles restricting heavy firefighting vehicle access) (Arda et al., 2025; Uthappa et al., 2025; Vujović et al., 2025).

The final phase of the spatial synthesis computationally overlays the GeoAI-driven Hazard continuous surface map with the BWM-derived multidimensional Vulnerability matrix at the precise 30x30 meter cellular level, generating the comprehensive Potential Forest Fire Risk Map. Moving beyond probabilistic risk mapping, high-resolution spatial intersection algorithms were applied to this final matrix to explicitly quantify deterministic disaster exposure. This spatial overlay process systematically intersects the continuous risk zones with discrete urban lifelines, precisely evaluating the areal distribution in hectares for polygon geometries (residential WUI and industrial zones), linear distribution in kilometers for line geometries (logistics and evacuation transportation networks) and point-based numerical distributions for critical facilities (hospitals, schools, fire stations). This final methodological integration converts complex geospatial data into the concrete exposure statistics necessary to prioritize Disaster Risk Reduction (DRR) strategies.

4. RESULTS

4.1 GeoAI Hazard Modeling and Feature Importance

The probability-based wildfire hazard models were developed utilizing advanced ensemble learning architectures, specifically XGBoost. The algorithm successfully captured the highly non-linear and multidimensional relationships between historical fire occurrences and complex environmental conditions. The XGBoost model achieved an overall accuracy of 68.75%, with average precision, recall, and F1-score values of 0.72, 0.54, and 0.58, respectively. Given the extreme spatial heterogeneity of the Marmara Region which encompasses diverse climatic transition zones, rugged topographic barriers and intricately fragmented land cover this performance indicates a robust capacity for reliably mapping physical ignition probabilities.

To transition the predictive architecture from a conventional black-box model to a transparent and interpretable Spatial Decision Support System (SDSS), feature importance analyses were conducted (Tonbul 2024; Tonbul and Veraverbeke 2026). Figure 4 illustrates the relative contribution and ranking of each spatial variable integrated into the hazard output.

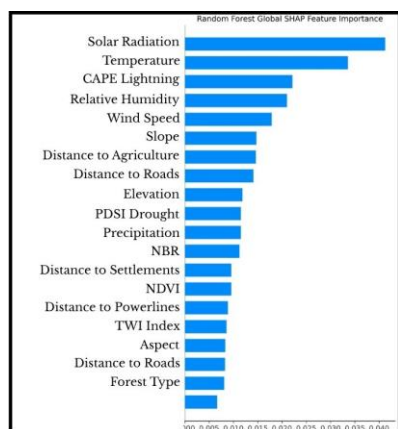


Figure 4. Feature Importance ranking derived from the GeoAI model, indicating the primary drivers of wildfire hazard in the study area.

The feature importance analysis definitively reveals that anthropogenic pressures are the absolute dominant drivers of wildfire ignition in the Marmara Region. Distance-based spatial metrics particularly proximity to road networks, residential settlements and agricultural areas consistently ranked among the most influential contributing factors. This mathematically confirms the hypothesis that the vast majority of fire ignitions in this specific geography are human-induced, validating the critical role of WUI dynamics. Conversely, while anthropogenic factors supply the ignition source, climatic and topographic variables (such as maximum temperature anomalies, solar radiation and steep slopes) exhibited high feature importance by functioning as critical thermodynamic catalysts. These environmental variables dictate the rate of spread (ROS) and fuel flammability immediately after an ignition occurs. Interestingly, variables such as distance to power transmission lines demonstrated a moderate influence the model interprets them as localized, specific ignition nodes rather than widespread, continuous regional drivers.

4.2 Vulnerability Assessment Findings

The spatial vulnerability matrix, structured and optimized via the BWM, provided a mathematically consistent and literature-backed hierarchy of the elements at risk (Arda et al., 2025; Batur et al., 2025; Vujović et al., 2025). The linear optimization results identified Distance to Forest Areas as the most critical (best) criterion, receiving the highest overarching weighting coefficient of approximately 0.19. This statistical dominance confirms that the highest degree of ecological degradation and structural exposure occurs at the direct boundaries of the forest ecosystem, where thermal radiation and direct flame contact are absolute. Furthermore, logistical and operational factors, specifically Distance to Fire Stations and Slope, received critically high weights (approximately 0.10 each). This emphasizes the profound vulnerability created by operational inaccessibility steep topographies and geographic isolation from response centers create tactical barriers that prevent heavy firefighting machinery from intervening, thereby allowing initial ignitions to rapidly evolve into uncontrollable crown fires. In contrast, socio-economic factors, such as Income Level, were ranked as the least influential (worst) criteria in the matrix. While socio-economic resilience remains absolutely vital for post-fire societal recovery and reconstruction, the BWM model correctly identified that these factors do not physically alter the immediate trajectory or destructiveness of the advancing fire front. The vulnerability map is given in Figure 5.

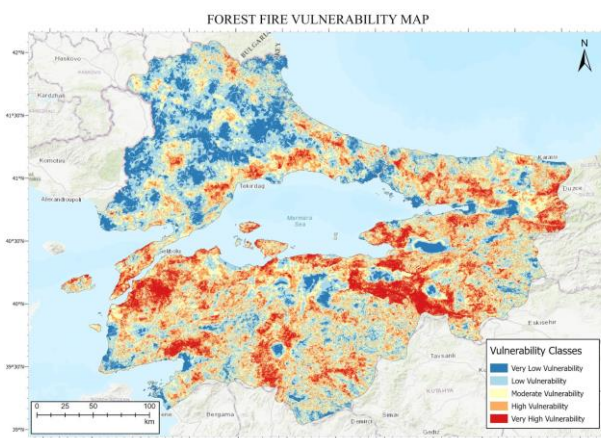


Figure 5. Multidimensional spatial vulnerability map structured via the BWM, highlighting areas with critical socio-ecological and infrastructural exposure.

Additionally, the hazard map generated using the XGBoost model is presented in Figure 6.

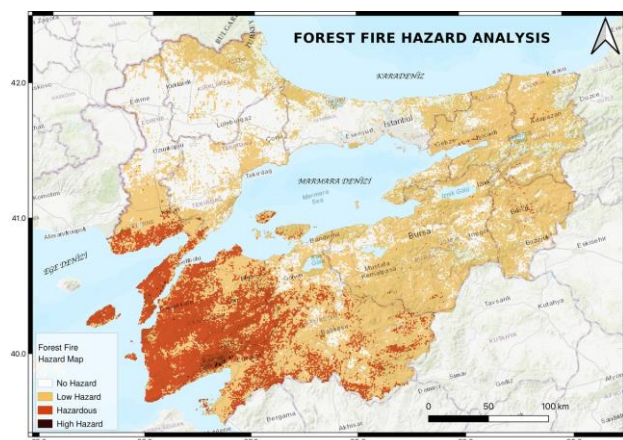


Figure 6. The hazard map generated using the XGBoost model.

5. CONCLUSIONS

The exponentially increasing frequency and intensity of forest fires, driven by global climate anomalies and severe anthropogenic pressures, unequivocally necessitate a paradigm shift from traditional, reactive fire suppression toward proactive disaster risk management. This study successfully engineered an explainable GeoAI-based wildfire risk analysis framework tailored for the complex socio-ecological landscape of the Marmara Region. By seamlessly integrating multi-source geospatial data, advanced machine learning architectures and spatial Multi-Criteria Decision Making BWM, the proposed methodology achieved high spatial accuracy in predicting fire ignition probabilities. Concurrently, it established a mathematically consistent hierarchy of urban, infrastructural and ecological vulnerabilities. A defining achievement of this research was the utilization of feature importance analysis, which effectively transitioned the predictive model from a conventional black-box algorithm into a highly transparent decision-making tool. This approach empirically confirmed that anthropogenic activities and physical proximity to road networks are the absolute primary triggers of fire events in the region, validating the critical role of human geography in regional fire regimes.

The high-resolution spatial exposure analysis conducted in this study revealed that wildfire risk in the Marmara Region drastically transcends isolated ecological damage it poses severe, cascading threats to the entire urban metabolism. The continuous and historically unregulated expansion of WUI zones has critically trapped substantial residential populations, vital educational institutions and healthcare facilities within very high-risk areas, signaling a deepening socio-demographic crisis that complicates mass evacuation. Furthermore, the extreme spatial exposure of major industrial and mining facilities highlights a catastrophic potential for Natural Hazard Triggering Technological Disasters (Natech), where a wildfire could precipitate secondary chemical leaks and macro-economic supply chain collapse. Ecologically, the alarming vulnerability of over one million hectares of primary drinking water basins threatens long-term urban water security due to the severe risks of post-fire soil erosion, heavy metal contamination and toxic ash transport. Additionally, the predicted tactical failure of extensive transportation networks which double as ignition corridors and sole escape routes underscores the urgent need for

dynamic, risk-aware evacuation planning to prevent deadly logistical bottlenecks.

Ultimately, the developed framework functions not merely as an academic exercise, but as a highly actionable Spatial Decision Support System (SDSS) for disaster management authorities such as AFAD and local municipalities. It provides local governments with the deterministic spatial intelligence necessary to implement vital policy interventions. These actionable recommendations include the immediate establishment of combustible-free ecological buffer zones around critical WUI settlements and industrial facilities, the optimization of emergency resource allocation and the critical updating of regional emergency response protocols. Looking forward, integrating these explainable GeoAI models into broader smart city infrastructures could support the development of advanced wildfire monitoring and risk management systems. Future studies and municipal implementations should focus on coupling this static predictive framework with Internet of Things (IoT) sensor networks and real-time meteorological data streams. Developing such dynamic Digital Twins and Real-Time Early Warning Systems represents the ultimate critical step toward maximizing urban adaptation capacities and building truly sustainable, smart and resilient cities capable of withstanding the escalating impacts of global climate change.

Acknowledgements

This study was conducted as part of the MARAP project, carried out in collaboration between Istanbul Technical University and Türkiye Disaster and Emergency Management Presidency (AFAD).

References

- Arda, T., Bayrak, O.C. & Uzar, M. Analyzing Coastal Vulnerability Using Analytic Hierarchy Process and Best–Worst Method: A Case Study of the Marmara Gulf Region. *Arab J Sci Eng* 50, 1851–1869 (2025). <https://doi.org/10.1007/s13369-024-09128-w>
- Batur, M., Karaman, H., Alkan, R. M., & Ozener, H. (2025). Mapping Social Vulnerability to Nuclear Accidents: a Comparative Framework Using BWM and AHP Methods. *Applied Spatial Analysis and Policy*, 18(1), 45. <https://doi.org/10.1007/s12061-025-09649-3>
- Eskandari, S., Amiri, M., Sādhāsivam, N., & Pourghasemi, H. R. (2020). Comparison of new individual and hybrid machine learning algorithms for modeling and mapping fire hazard: a supplementary analysis of fire hazard in different counties of Golestan Province in Iran. *Natural Hazards*, 104(1), 305–327. <https://doi.org/10.1007/s11069-020-04169-4>
- General Directorate of Forestry (GDF). (n.d.). *Ormançılık İstatistikleri*. <https://www.ogm.gov.tr/tr/e-kutuphane/kitaplik/Ormancilik-istatistikleri>
- Kazemi Veisari, P., Motieyan, H., & Qaderi, F. (2025). Spatial assessment of surface water vulnerability through MCDM and open-source data. *Environmental Monitoring and Assessment*, 197(8), 907. <https://doi.org/10.1007/s10661-025-14357-z>
- Khan, S. M., Shafi, I., Butt, W. H., Diez, I. D. L. T., Flores, M. A. L., Galán, J. C., & Ashraf, I. (2023). A systematic review of disaster management systems: approaches, challenges, and

- future directions. *Land*, 12(8), 1514. <https://doi.org/doi.org/10.3390/land12081514>
- O'Connor, C. D., Thompson, M. P., & Rodríguez y Silva, F. (2016). Getting Ahead of the Wildfire Problem: Quantifying and Mapping Management Challenges and Opportunities. *Geosciences*, 6(3), 35. <https://doi.org/10.3390/geosciences6030035>
- Özcan, H., Kesen, E., Şahin, S. (2025). Design of smart ground and air systems that monitor critical missions: example system forest fire. *Pamukkale University Journal of Engineering Sciences*, 31(2), 212-219. <https://doi.org/10.5505/pajes.2024.90167>
- Pourghasemi, H. R., Pouyan, S., Bordbar, M., Golkar, F., & Clague, J. J. (2023). Flood, landslides, forest fire, and earthquake susceptibility maps using machine learning techniques and their combination. *Natural Hazards*, 116(3), 3797-3816. <https://doi.org/10.1007/s11069-023-05836-y>
- Shi, C., & Zhang, F. (2023). A forest fire susceptibility modeling approach based on integration machine learning algorithm. *Forests*, 14(7), 1506. <https://doi.org/10.3390/f14071506>
- Sivrikaya, F., & Demirel, D. (2025). Fire risk mapping using machine learning method and remote sensing in the Mediterranean region. *Advances in Space Research*, 75(7), 5402-5419. <https://doi.org/10.1016/j.asr.2025.01.050>
- Tonbul, H. (2024). Integrating ensemble machine learning and explainable AI for enhanced forest fire susceptibility analysis and risk assessment in Türkiye's Mediterranean region. *Earth Science Informatics*, 17(6), 5709-5731. <https://doi.org/10.1007/s12145-024-01480-7>
- Tonbul, H., & Veraverbeke, S. (2026). Machine-learning wildfire susceptibility mapping with SHAP-based explainability in Türkiye's fire-prone regions. *Stochastic Environmental Research and Risk Assessment*, 40(1), 2. <https://doi.org/10.1007/s00477-025-03136-4>
- Uthappa, A. R., Das, B., Raizada, A., Kumar, P., Jha, P., & Prasad, P. V. (2025). Forest fire susceptibility mapping using multi-criteria decision making and machine learning models in the Western Ghats of India. *Journal of environmental management*, 379, 124777. <https://doi.org/10.1016/j.jenvman.2025.124777>
- Vujović, F., Valjarević, A., Durlević, U., Morar, C., Grama, V., Spalević, V., Milanović, M., Filipović, D., Čulafić, G., Gazdić, M., Batočanin, N., Barović, G., Golijanin, J., Radovanović, D., Bačević, N., Šiljeg, A. (2025). A Comparison of the AHP and BWM Models for the Flash Flood Susceptibility Assessment: A Case Study of the Ibar River Basin in Montenegro. *Water*, 17(6), 844. <https://doi.org/10.3390/w17060844>
- Yılmaz, O. S., Oruç, M. S., Ateş, A. M., & Güngen, F. (2021). Orman yangın şiddetinin Google Earth Engine ve coğrafi bilgi sistemleri kullanarak analizi: Hatay-Belen örneği. *Journal of the Institute of Science and Technology*, 11(2), 1519-1532. <https://doi.org/10.21597/jist.817900>
- Zerouali, B., Santos, C. A. G., Qaysi, S., da Silva, R. M., Alarifi, N., Bailek, N., ... & Youssef, Y. M. (2025). Advanced forest fire risk mapping: Combining Sentinel-2 MSI data with hybrid machine learning in Similipal Biosphere Reserve. *Forest Ecology and Management*, 594, 122931. <https://doi.org/10.1016/j.foreco.2025.122931>