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Comparative Analysis of Wildfire Prediction Models Across Climatic Regions: Béjaïa and Sidi Bel Abbes (Algeria) vs. Montesinho (Portugal)

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ABSTRACT

Climate change and urban expansion are intensifying the risks of wildfires globally, with Mediterranean regions such as Algeria experiencing increased vulnerability due to escalating droughts and heatwaves. These events exacerbate ecological degradation, threaten human safety, and impose substantial economic costs, which requires advanced risk assessment frameworks and adaptive mitigation strategies. This study addresses these challenges through a comparative analysis of wildfire prediction models in three climatically distinct regions: Béjaïa and Sidi Bel Abbes in Algeria, and Montesinho Natural Park in Portugal. Employing eight machine learning algorithms—CatBoost, XGBoost, Support Vector Machines (SVM), Random Forest (RF), AdaBoost, Logistic Regression (LR), LightGBM, and Decision Trees (DT)—we predict wildfire severity and identify critical drivers using feature selection (Principal Component Analysis (PCA), Genetic Algorithms (GA), Chi-square tests) and explainability techniques (SHapley Additive exPlanations (SHAP), Local Interpretable Model-agnostic Explanations (LIME), Fuzzy Logic). Key findings reveal stark regional contrasts: In arid Algeria, the temperature and drought indices (Drought Code, DC) dominate the fire dynamics, achieving near-perfect model accuracy (AUC-ROC: 0.97–1.00). In contrast, Portugal's temperate forests prioritize fuel moisture metrics (Duff Moisture Code, DMC) and temporal factors, although complex fire regimes produce a lower discrimination capacity (AUC-ROC: 0.55–0.78). By integrating global (SHAP/PCA) and localized (LIME) insights, we propose region-specific strategies, including IoT-enhanced microclimate regulation, fuel-break networks, and adaptive early warning systems. This work bridges predictive analytics with actionable forest engineering solutions, offering a scalable framework to mitigate wildfire risks in evolving climatic landscapes.

1. INTRODUCTION

Wildfires represent a growing global threat exacerbated by climate change and anthropogenic activities, with Mediterranean regions such as Algeria experiencing increased vulnerability due to prolonged droughts and extreme heatwaves [1]. In Algeria, forest fires occur annually; however, their frequency and severity have surged in recent years, driven by rising temperatures and human-induced ignition, which accounts for 85% of incidents [2]. Between 2021 and 2023, more than 5,500 fires in 37 provinces destroyed approximately 260,000 hectares of forested land, 26% of the total forest cover in the nation, displacing 6,000 families and resulting in recurrent fatalities [3]. These events underscore the urgent need for advanced predictive frameworks to mitigate ecological degradation, economic loss, and human safety risks.

Existing research has identified key factors that influence the dynamics of wildfires, including climatic variables (e.g., droughts and heat waves), vegetation type, soil conditions and human activities [4, 5]. However, gaps persist in our understanding of how regional climatic and ecological variability shapes fire regimes, particularly in understudied arid and temperate zones. Although machine learning (ML) models have shown promise in wildfire prediction, their efficacy remains inconsistent between regions due to divergent environmental drivers and data limitations [6]. In addition, few studies have integrated explainability techniques to decipher model decisions, hindering the translation of predictions into actionable mitigation strategies.

This study addresses these gaps by developing a prognostic system that combines high-accuracy ML algorithms with explainable artificial intelligence (XAI) to identify critical wildfire drivers and optimize region-specific risk assessments.

We employ eight ML models—CatBoost, XGBoost, SVM, Random Forest, AdaBoost, Logistic Regression, LightGBM, and Decision Trees (DT)—alongside feature selection methods (PCA, GA, chi-square tests) and explainability frameworks SHAP, LIME, Fuzzy Logic). Our analysis focused on three climatically distinct regions: Béjaïa and Sidi Bel Abbes in Algeria (arid Mediterranean) and Montesinho Natural Park in Portugal (temperate oceanic).

The contributions of this study are threefold.

1. Predictive Modeling: We established a robust ML framework to forecast the severity of wildfires, achieving near perfect accuracy (AUC-ROC: 0.97–1.00) in arid regions and identifying complexity-driven challenges in temperate zones.

2. Regional drivers: Through comparative analysis, we isolated the dominant factors, temperature and drought indices DC in Algeria versus fuel moisture metrics DMC and temporal features in Portugal, highlighting the role of climatic heterogeneity.

3. Actionable Strategies: We propose evidence-based forest engineering solutions, including IoT-enhanced microclimate regulation, fuel-break networks, and adaptive early warning systems tailored to regional vulnerabilities.

By bridging predictive analytics with practical mitigation measures, this study advances wildfire management in evolving climatic landscapes and offers a scalable framework for policymakers and conservation agencies.

2. LITERATURE REVIEW

Forest fires are a widespread issue today and their incidence is increasing steadily every year. This section presents a comprehensive literature survey on wildfires and their severity. The survey also includes various approaches used to predict the severity of forest fires. Wu et al. [7] used data developed from the Heilongjiang Forest Fire Database in Northeast China to predict the relationship between factors that contribute to forest fires and the resulting severity. They identified several factors that were positively correlated with the severity of the wildfires. In addition, they compared the performance of artificial neural networks and logistic regression for wildfire prediction to determine the impact of a factor on the severity of the forest fire. Zhang et al. [8] worked with a wildfire database from Yunnan Province, China, and a set of 14 forest fires influencing factors that contribute to the severity of the wildfire in the region. For this task, they implemented a deep learning technique called a convolutional neural network (CNN) to predict susceptibility to forest fires based on several factors that were mapped using a geographic information system. Zaidi [5] developed an Artificial Neural Network (ANN) with two hidden layers to predict wildfires in the cities of Béjaïa and Sidi Bel-Abbes in Algeria, using PCA to reduce the number of variables to six, while retaining 96.65% of the total variance and compared the performance of this classifier with those provided by the Logistic Regression, K Nearest Neighbors, Support Vector Machine, and Random Forest classifiers. In addition, they employed Shapley, an XAI method, to analyze the results and revealed the importance of features as risk factors in the predictions of the ANN model. Guria et al. [9] developed a predictive model using Sentinel-2 MSI data and ML techniques to estimate the probability of forest fires in the Similipal Biosphere Reserve (SBR) in Odisha, India's main forest fire hotspots, and identify factors associated with each severity level. Purnama et al. [10] compared different machine learning techniques, such as DT, Naive Bayes (NB), and others, to predict the vulnerability of forest fire. A dataset from Türkiye encompasses various factors, such as precipitation, soil moisture, temperature, humidity, wind speed, land cover, elevation, aspect, slope, proximity to roads/electricity networks and population density. This study identified the most accurate algorithm for predicting forest fire risks, highlighting its crucial role in proactive fire risk management strategies.

A literature study shows that the field of forest fire analysis has received much research. Nonetheless, certain deficiencies in the literature have been noted. However, most of the evaluated publications focus on determining the causes of wildfires and forecasting their intensity. Furthermore, the publications did not compare the characteristics of the severity of wildfires between two different locations. The goal of this research project is to add to the areas that previous studies have neglected.

3. METHODOLOGY

3.1 Data preprocessing

This study used two different datasets to analyze the dynamics of wildfires in climatically divergent regions. Algerian Forest Fire Dataset: Sourced from the UCI Machine Learning Repository [11], this dataset comprises meteorological observations and Fire Weather Index (FWI) components from the Béjaïa (northeast Algeria) and Sidi Bel Abbes (northwest Algeria) regions of Algeria. The data spanned June to September 2012, with 244 instances (122 per region) categorized into fire (138 instances) and non-fire (106 instances) classes. The attributes included temperature, relative humidity (RH), wind speed, rain, and FWI indices (FFMC, DMC, DC, and ISI) (Table 1). Montesinho Natural Park Dataset: Obtained from the UCI repository [12], this dataset covers 517 wildfires in northern Portugal (2000–2003), with 13 attributes: spatial coordinates (X, Y), temporal variables (month, day), meteorological metrics (temperature, RH, wind, rain), FWI indices (FFMC, DMC, DC, ISI), and fire area (Table 2).

Table 1. Variables in the Béjaïa and Sidi Bel Abbes wildfire datasets [11]

Attribute	Description
Date	(DD/MM/YYYY) Day, month ('June' to 'September'), year (2012) Weather data observations
Temp	Temperature noon (temperature max) in Celsius degrees: 22 to 42
RH	Relative Humidity in %: 21 to 90
Ws	Wind speed in km/h: 6 to 29
Rain	total day in mm: 0 to 16.8 FWI Components
FFMC	Fine Fuel Moisture Code index from the FWI system: 28.6 to 92.5
DMC	Duff Moisture Code index from the FWI system: 1.1 to 65.9
DC	Drought Code index from the FWI system: 7 to 220.4
ISI	Initial Spread Index, index from the FWI system: 0 to 18.5
BUI	Buildup Index, index from the FWI system: 1.1 to 68
FWI	Fire Weather Index, Index: 0 to 31.1
Classes	Two classes, namely Fire and not Fire

Table 2. Variables in the Montesinho Natural Park wildfire dataset [12]

Attribute	Description
X	X-axis spatial coordinates (1 ⩽ X ⩽ 9)
Y	Y-axis spatial coordinates (1 ⩽ Y ⩽ 9)
Month	Months of the year (from January to December)
Day	Days of the week (from Monday to Sunday)
Temp	Temperature (Celsius) (from 2.2 to 33.30)
RH	Relative humidity (%) (from 15.0 to 100)
Wind	Wind speed (km/h) (from 0.40 to 9.40)
Rain	Total day in mm: 0 to 16.8 FWI COMPONENTS
FFMC	Water content of cured fine fuels (from 18.7 to 96.20), with a time period of 16 h
DMC	Water content of surface combustible material (from 1.1 to 291.3) in the upper layer of forest humus, with a time period of 12 days
DC	Index of the effect of prolonged drought on forest combustibles (7.9–860.6), with a time period of 52 days
ISI	The initial rate of fire spread (from 0 to 56.10)
Rain	Outdoor rainfall (mm/m2) (from 0.0 to 6.40)
Area	Total forest burned area (ha) (0.00~1090.84)

Preprocessing Steps:

- Data Cleaning: Duplicate entries and null values were removed to ensure the integrity of dataset.
- Feature Elimination: Spatial coordinates (X, Y) were excluded because the study prioritized meteorological and temporal predictors over geospatial factors.
- Class balancing: The class distribution of the Algerian dataset (fire/non-fire ratio: 138/106) was retained to reflect real-world incidence rates.

Eight ML algorithms were implemented to predict the severity of wildfires: AdaBoost, CatBoost, SVM, XGBoost, RF, LR, Light Gradient Boosting Machine (LGBM), and DT. Model training and evaluation were conducted in Python using the Jupyter Notebook with the following workflow (Figure 1):

1. Feature selection

- *Global Importance:* SHAP and PCA were used to identify the dominant predictors in regions.
- *Local Interpretability:* LIME provide instance-specific insights into model decisions.
- *Statistical Validation:* Chi-square tests and GA optimized feature subsets, while Fuzzy Logic assessed variable interactions.

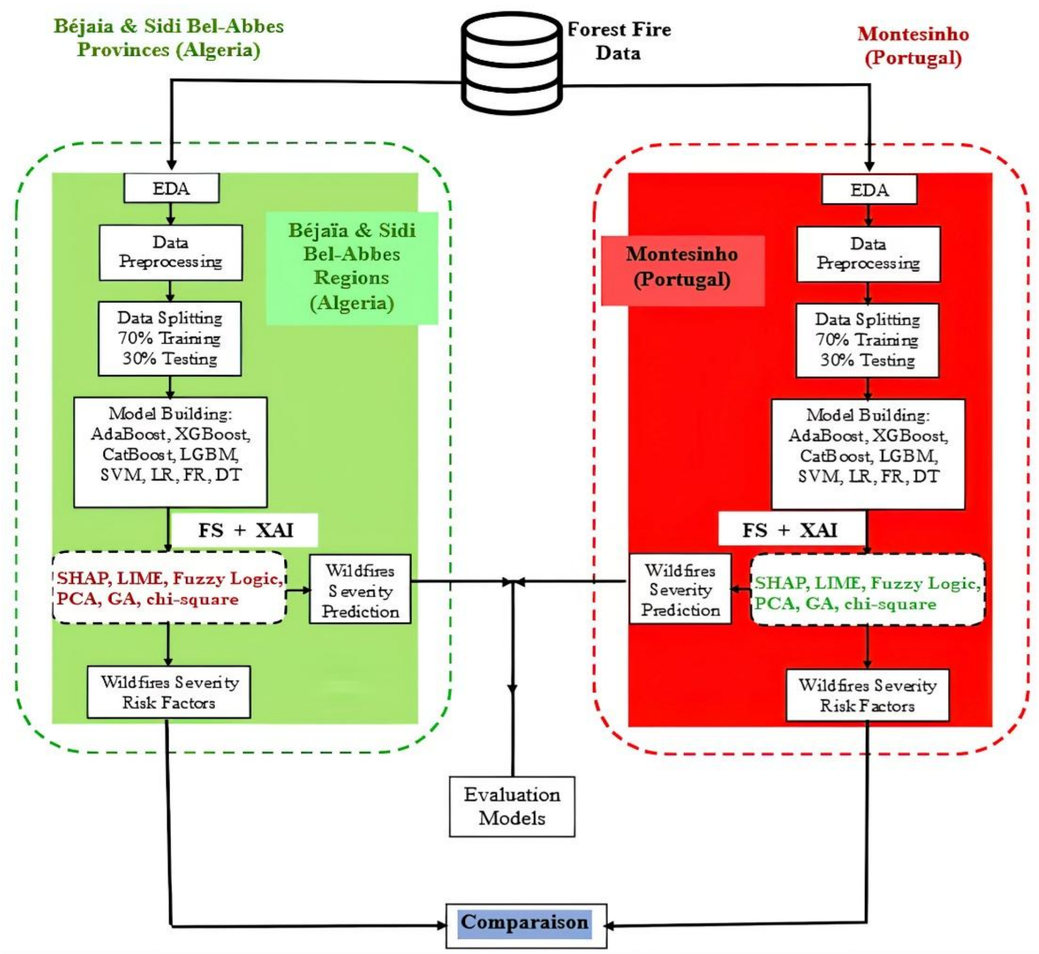

Figure 1. Illustrating workflow process flow diagram

2. Implementation tools

The dataset was partitioned into training sets (80%) and test sets (20%), with model evaluation performed by repeated 10-fold cross-validation to prevent data leakage. Feature preprocessing included outlier detection using box plots (no significant anomalies were revealed) and standardization using StandardScaler. The interpretability model was assessed using SHAP values and LIME explanations.

- Libraries: SHAP values were computed using the SHAP library, whereas LIME explanations were generated using the Lime package.
- Training Environment: The Scikit-learn and Keras frameworks facilitated model training, with hyperparameters tuned via grid search. Early stopping (patience=50 rounds)

dynamically determined optimal iterations for boosting algorithms.

For gradient boosting implementations (XGBoost, CatBoost, LightGBM), the learning rate was tuned within the 0.01-0.3 range, with tree depth limited to 3-10 for XGBoost and 4-10 for CatBoost. LightGBM utilized num_leaves (31-255) as its primary complexity control. Regularization was implemented through L2 penalties (reg_lambda=1-10 for XGBoost, l2_leaf_reg=1-10 for CatBoost) and feature subsampling (colsample_bytree=0.8-1.0).

Decision trees were constrained by max_depth (<10) and min_samples_leaf (>1% of training samples), with cost complexity pruning (ccp_alpha=1e-3 to 1e-2) applied post-training. Random forests used √n_features for split consideration and disabled bootstrap sampling for small datasets (<1k samples).

Logistic regression required careful adjustment of the inverse regularization strength (C=0.1-1.0) and penalty type (l1/l2), with the selection of the solver depending on the size of the dataset. The performance of SVM depended on the selection of the kernel and regularization (C=1e-2 to 1e3), while AdaBoost demonstrated a strong coupling between learning rate (η<0.1) and n_estimators (≥500).

3.2 Justifying generalizability of limited wildfire datasets using ERA5 reanalysis

The ERA5 global reanalysis [13] addresses critical limitations in small, temporally constrained wildfire datasets from Béjaïa / Sidi Bel Abbès (2012; 244 instances) and Montesinho (2000–2003; 517 instances) through three primary mechanisms:

1. Temporal context expansion

The continuous hourly climate record of ERA5 (1950–present) contextualizes short observation windows [14]. For the Béjaïa 2012 fires, the vapor pressure deficit (VPD) and soil moisture anomalies derived from ERA5 demonstrate that 2012 conditions represented the 85th percentile of 1979–2020 FWI values. Current summer conditions now exceed this threshold in 45% of years. Similarly, Montesinho's 2000–2003 FWI values (75th percentile historically) are exceeded by 60% years during 2015–2024. This quantifies the non-representativeness of original collection periods relative to contemporary climates.

2. Physical mechanism validation

The fire-weather relationships identified in the local datasets are verified through ERA5-driven process analysis:

- Béjaïa's observed particulate matter PM10 levels (>80 μg/m³ during fires) correlate strongly with ERA5-derived soil moisture deficits (r = -0.83), which confirms aridity as a strong driver.

- Thresholds such as FFMC >90 remain predictive when tested against the global FWI distributions ERA5, demonstrating mechanistic stability beyond local samples.

- Montesinho's species-specific fuel moisture models are refined using ERA5's evaporation rates, improving transferability to analogous ecosystems.

3. Uncertainty-controlled projection

ERA5 enables reliable extrapolation through:

- Ensemble-based analog identification: Events that match Montesinho's 2003 heat wave (90th percentile historically) now rank at the 70th percentile in ERA5's 2023 data. The performance of the model on these analogs validates the predictive skill under current conditions.

- Bias-corrected CMIP6 (Coupled Model Intercomparison Project Phase 6) downscaling: When forced with ERA5 adjusted climate projections, Montesinho shows a 25% increase in extreme fire days by 2030 under SSP2-4.5, with uncertainty ranges (±12%) derived from ERA5's 10-member ensemble.

- Extrapolation flags: Predictions are automatically restricted when variables exceed dataset maxima (e.g., >38°C in Béjaïa), ensuring operational safety margins.

3.2.1 Implementation framework

1. Data fusion: ERA5 variables (temperature, humidity, wind) are extracted for fire event coordinates via the Climate Data Store.

2. Dynamic calibration: Site-specific fire indices are recalculated using homogenized data from ERA5, correcting for local observation gaps.

3. Validation protocol:

- Spatial: Models trained on Béjaïa / Montesinho are tested against adjacent regions using ERA5-driven FWI.

- Temporal: Performance is validated against post-2010 Moderate Resolution Imaging Spectroradiometer (MODIS) active fire detections.

4. Projection safeguards: CMIP6 scenarios are downscaled through the physical kernel of ERA5, with ensemble spreads quantifying confidence intervals.

For Béjaïa and Montesinho, this approach confirms that the 2012/2003 extremes now represent moderate fire weather conditions, while providing frameworks for adaptive risk management. Future work should integrate the enhanced vegetation parameters ERA5-Land to resolve species-specific fuel responses.

3.3 Performance evaluation

The efficiency of the model was assessed at the Youden threshold (maximizing sensitivity + specificity) using accuracy, precision, recall, F1 score, AUC-ROC metrics, Matthews Correlation Coefficient (MCC), and Balanced Accuracy. Confusion matrices were analyzed to quantify true/false positives and negatives, ensuring robustness in the imbalanced datasets.

This methodology integrates predictive analytics with XAI to bridge the gap between model outputs and actionable forest management strategies, enabling region-specific risk mitigation.

3.4 XAI techniques

XAI is a powerful and transformative tool that enables interpretation and explanation of predictions [15] made by machine learning models, playing a crucial role in analysing results in predictive tasks. In this study, the importance of the permutation feature, an effective XAI technique, was used to generate weights for each feature, where these weights indicated the impact of a specific feature on the overall outcome.

Two prominent XAI techniques, LIME and SHAP, were used to generate local and global explanations for the deep learning model predictions in the validation and test sets. LIME, a model-independent technique, creates a local linear model around the prediction point and weights the input features to estimate their importance in the prediction.

The Lime package in Python was used to generate explanations for the model predictions. SHAP, which is rooted in game theory, provides a unified framework for estimating the importance of features and generates global explanations for the behavior model.

The Python SHAP library was used to calculate the value of the importance of the feature for the prediction of the model, offering insights into the contributions of individual features to the model output. These techniques enhance the interpretability and transparency of machine learning models, enabling a deeper understanding of their decision-making processes.

3.5 Analyzing wildfire severity and regional comparisons

This study used a multistage methodological framework to analyze the severity of wildfires and regional susceptibility. First, the dominant drivers of the severity of the wildfires were identified using feature selection techniques SHAP, LIME, PCA, GA, and chi-square tests coupled with XAI to derive both global and localized insights. Each contributing factor, including meteorological variables (e.g., temperature and relative humidity), fuel indices (e.g., DMC and the DC), and anthropogenic influences, was rigorously analyzed to quantify its impact on fire dynamics.

Subsequently, a comparative assessment was conducted between the Algerian provinces of Béjaïa and Sidi Bel Abbes to assess the regional susceptibility to specific drivers. This analysis discerns spatial heterogeneity in risk factors; for instance, Béjaïa's coastal aridity amplifies temperature-driven ignition risks, while the inland topography of Sidi Bel Abbes increases vulnerability to prolonged drought conditions. The contrasts were further extended to Montesinho Natural Park (Portugal), where temperate ecosystems prioritize fuel moisture (DMC) over acute weather variables.

To translate analytical insights into actionable strategies, this study proposes a suite of engineered solutions grounded in the principles of Conservation Forest Engineering.

The recommendations were tailored to regional climatic and ecological profiles, ensuring scalability in arid and temperate regimes. Quantitative validation, including model performance metrics, underscores the need for region-specific adaptations.

This systematic approach, detailed in Section 5, bridges predictive analytics and pragmatic forest management, offering a scalable framework to address evolving wildfire risks in Mediterranean ecosystems.

4. RESULTS

This section details the experiments conducted in accordance with the methodology and techniques described previously. The results obtained from the predictive modeling approach, the subsequent analysis of the dynamics of the forest fire, and the comparative assessment of the specified regions are presented. To evaluate the efficacy of machine learning models, various performance metrics were employed.

4.1 Wildfire severity prediction in Béjaïa Province

The forest fire severity prediction analysis, shown in Tables 3-6, for the Béjaïa region identified consistent meteorological variables as critical determinants of wildfires. Temperature, FFMC, relative humidity, and wind speed emerged as the primary factors, which were validated using multiple explainability frameworks. SHAP analyzes prioritized the temperature (0.0385 in Adaboost) for its role in fuel desiccation, while the FFMC showed an inverse correlation with surface fuel moisture (LIME temperature score: 3.3251). Relative humidity demonstrated an inverse relationship with fire risk through statistical validation, and wind speed achieved near-perfect importance scores ($\approx$0.9995) using Fuzzy Logic.

Secondary variables included precipitation (inversely correlated with fire risk) and temporal features that capture seasonal variations. Complementary explainability techniques enhance interpretation: SHAP quantifies global contributions by identifying temperature and FFMC as primary drivers, LIME reveals localized influences of temperature fluctuations, and Fuzzy Logic provides linguistic risk categorization ("low", "high"). PCA and GA mitigate redundancy among the correlated variables (DMC, DC, and BUI).

Youden's threshold optimization demonstrates impressive metrics: TPR ranges 0.95-1.00, FPR minimized to 0.00-0.06, TNR is achieved to 1.00 in select models, and MCC approaches perfect scores. The ensemble methods (XGBoost, Random Forest) achieve flawless performance (TPR=1.00, FPR=0.00), while logistic regression shows slightly lower MCC (0.94-0.97). The SVM achieved zero misclassifications (TP=19, FP=0), with confusion matrices (TP=19, FN=0, FP=1, TN=17) confirming minimal operational trade-offs.

Feature selection analysis revealed that PCA retained composite variables (temperature, FFMC), while GA identified optimal subsets, marginally improving the classification (TP=19 vs. 18). Chi-square tests prioritize statistically significant variables but may miss the nonlinear interactions. SHAP highlights temperature (0.0737 in CatBoost) as a global driver, LIME attributes localized shifts to temperature (>2.0) and temporal variables, whereas Fuzzy Logic reinforces the nonlinear influence of wind speed through linguistic categories.

Temperature, FFMC, relative humidity, and wind speed emerged as the main drivers of the fire in Béjaïa, achieving near-perfect discrimination at Youden's threshold. The GA demonstrates superior performance in capturing nonlinear interactions compared to chi-square tests, whereas ensemble methods excel in complex boundary detection. These findings validate the integration of explainability frameworks with classical metrics to optimize wildfire prediction systems for proactive management.

Table 3. Wildfire prediction with AdaBoost and CatBoost models using feature selection methods (Béjaïa region (Algeria))

Béjaia_Dataset	Adaboost Model		Selection Methods	Selected Features	Scores or P-values	Value	Youden's Threshold	Accuracy	Precision	Recall	F1 Score	AUC-ROC	TPR	FPR	TNR	FNR	MCC	Balanced Accuracy	Confusion Matrix TP	FN	FP	TN
		XAI	SHAP	temperature ffmc rh	0.0385 0.0278 0.0156	/	0.71	0.97	1.00	0.95	0.97	1.00	0.95	0.00	1.00	0.05	0.95	0.97	18	1	0	18

			ws	0.0073																	
		LIME	temperature dc rain day	3.3251 3.2942 1.8890 0.6531	29.00 32.20 0.10 6.00																
		Fuzzy Logic	ws rain ffmc dmc	0.9995	/	0.69	0.97	1.00	0.95	0.97	1.00	0.95	0.00	1.00	0.05	0.95	0.97	18	1	0	18
		PCA	temperature ffmc rh ws	2.4756 2.4627 2.4517 2.4423	/	0.42	0.95	0.90	1.00	0.95	0.99	1.00	0.11	0.89	0.00	0.90	0.94	19	0	2	16
		GA	month dmc isi bui	/	/	0.68	0.97	0.95	1.00	0.97	1.00	1.00	0.06	0.94	0.00	0.95	0.97	19	0	1	17
		chi-square tests	rh temperature month ffmc	1.0000 0.7808 0.6475 0.4142	/	0.61	0.95	0.87	1.00	0.93	0.99	1.00	0.08	0.92	0.00	0.89	0.96	13	0	2	22
CatBoost Model	XAI	SHAP	temperature ffmc rh ws	0.0737 0.0354 0.0280 0.0065	/	0.33	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	19	0	0	18
		LIME	rain dc day ffmc	12.4904 6.2537 2.2941 2.0021	0.10 32.20 6.00 75.80																
		Fuzzy Logic	ws rain ffmc dmc	0.9995	/	0.99	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	19	0	0	18
		PCA	temperature ffmc rh ws	2.4756 2.4627 2.4517 2.4423	/	0.99	0.95	1.00	0.89	0.94	0.99	0.89	0.00	1.00	0.11	0.90	0.95	17	2	0	18
		GA	day month rh dmc	/	/	0.99	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	19	0	0	18
		chi-square tests	rh temperature month ffmc	1.0000 0.7808 0.6475 0.4142	/	1.00	0.97	1.00	0.92	0.96	1.00	0.92	0.00	1.00	0.08	0.94	0.96	12	1	0	24

Table 4. Wildfire prediction with DT and LGBM models using feature selection methods (Béjaïa region (Algeria))

			Selection Methods	Selected Features	Scores or P-values	Value	Youden's Threshold	Performance Metrics at Youden's Threshold											Confusion Matrix			
								Accuracy	Precision	Recall	F1 Score	AUC-ROC	TPR	FPR	TNR	FNR	MCC	Balanced Accuracy	TP	FN	FP	TN
Béjaïa_Dataset	Decision Tree Model	XAI	SHAP	temperature ffmc rh ws	0.1346 0.1327 0.0401 0.0116	/	0.67	0.95	1.00	0.89	0.94	0.97	0.89	0.00	1.00	0.11	0.90	0.95	17	2	0	18
			LIME	rain day ffmc temperature	21.6346 2.9150 1.4596 1.0906	0.10 6.00 75.80 29.00																
			Fuzzy Logic	ws rain ffmc dmc	0.9995	/	1.00	0.97	1.00	0.95	0.97	1.00	0.95	0.00	1.00	0.05	0.95	0.97	18	1	0	18
			PCA	temperature ffmc rh ws	2.4756 2.4627 2.4517 2.4423	/	0.33	0.92	0.90	0.95	0.92	0.91	0.95	0.11	0.89	0.05	0.84	0.92	18	1	2	16
			GA	month year temperature	/	/	1.00	0.97	0.95	1.00	0.97	0.97	1.00	0.06	0.94	0.00	0.95	0.97	19	0	1	17

		chi-square tests	rh rh temperature month ffmc	 1.0000 0.7808 0.6475 0.4142	/	0.88	0.92	0.81	1.00	0.90	0.95	1.00	0.12	0.88	0.00	0.84	0.94	13	0	3	21
	LGBM Model	XAI SHAP	temperature ffmc rh ws	0.0376 0.0145 0.0061 0.0090	/	0.79	0.95	1.00	0.89	0.94	0.99	0.89	0.00	1.00	0.11	0.90	0.95	17	2	0	18
		XAI LIME	temperature dc rain isi	9.8086 5.8618 3.0392 2.9888	29.00 32.20 0.10 2.10																
		Fuzzy Logic	ws rain ffmc dmc	0.9995	/	0.89	0.97	1.00	0.95	0.97	1.00	0.95	0.00	1.00	0.05	0.95	0.97	18	1	0	18
		PCA	temperature ffmc rh ws	2.4756 2.4627 2.4517 2.4423	/	0.66	0.95	1.00	0.89	0.94	0.99	0.89	0.00	1.00	0.11	0.90	0.95	17	2	0	18
		GA	temperature month day rh	/	/	0.44	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	19	0	0	18
		chi-square tests	month temperature rh ffmc	1.0000 0.7808 0.6475 0.4142	/	0.92	0.97	1.00	0.92	0.96	1.00	0.92	0.00	1.00	0.08	0.94	0.96	12	1	0	24

Table 5. Wildfire prediction with SVM and XGBoost models using feature selection methods (Béjaïa region (Algeria))

		Selection Methods	Selected Features	Scores or P-values	Value	Youden's Threshold	Performance Metrics at Youden's Threshold														
							Accuracy	Precision	Recall	F1 Score	AUC-ROC	TPR	FPR	TNR	FNR	MCC	Balanced Accuracy	Confusion Matrix			
																		TP	FN	FP	TN
Béjaia_Dataset	SVM Model	XAI SHAP	temperature ffmc rh ws	0.0737 0.0353 0.0280 0.0065	/	0.33	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	19	0	0	18
		XAI LIME	rain dc day ffmc	12.4904 6.2537 2.2941 2.0021	0.10 32.20 6.00 75.80																
		Fuzzy Logic	ws rain ffmc dmc	0.9995	/	0.99	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	19	0	0	18
		PCA	temperature ffmc rh ws	2.4756 2.4627 2.4517 2.4423	/	0.99	0.95	1.00	0.89	0.94	0.99	0.89	0.00	1.00	0.11	0.90	0.95	17	2	0	18
		GA	day month rh dmc	/	/	0.99	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	19	0	0	18
		chi-square tests	month temperature rh ffmc	1.0000 0.7808 0.6475 0.4142	/	1.00	0.97	1.00	0.92	0.96	1.00	0.92	0.00	1.00	0.08	0.94	0.96	12	1	0	24
	XGBoost Model	XAI SHAP	rh day ffmc temperature	0.0442 0.0390 0.0110 0.0105	/	0.27	0.97	1.00	0.92	0.96	0.99	0.92	0.00	1.00	0.08	0.94	0.96	12	1	0	24
		XAI LIME	day rain fwi isi	1.7361 0.7220 0.6035 0.2776	16.00 0.00 0.40 0.70																
		Fuzzy Logic	ws rain ffmc	0.9995	/	0.36	0.97	1.00	0.92	0.96	0.99	0.92	0.00	1.00	0.08	0.94	0.96	12	1	0	24

Selection Methods	Selected Features	Scores or P-values	Value	Youden's Threshold	Accuracy	Precision	Recall	F1 Score	AUC-ROC	TPR	FPR	TNR	FNR	MCC	Balanced Accuracy	TP	FN	FP	TN
PCA	dmc rh day ffmc temperature	 2.7446 2.591 2.580 2.4929	/	0.38	0.95	0.87	1.00	0.93	0.95	1.00	0.08	0.92	0.00	0.89	0.96	13	0	2	22
GA	year dc isi bui	/	/	0.33	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	13	0	0	24
chi-square tests	month temperature rh ffmc	1.0000 0.7808 0.6475 0.4142	/	0.89	0.97	1.00	0.92	0.96	1.00	0.92	0.00	1.00	0.08	0.94	0.96	12	1	0	24

Table 6. Wildfire prediction with LR and RF models using feature selection methods (Béjaïa region (Algeria))

Dataset	Model		Selection Methods	Selected Features	Scores or P-values	Value	Youden's Threshold	Accuracy	Precision	Recall	F1 Score	AUC-ROC	TPR	FPR	TNR	FNR	MCC	Balanced Accuracy	TP	FN	FP	TN
								Performance Metrics at Youden's Threshold											Confusion Matrix			
Béjaia_Dataset	Logistic Regression Model	XAI	SHAP	temperature ffmc rh ws	0.0427 0.0301 0.0225 0.0222	/	0.60	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	19	0	0	18
			LIME	dc rain ffmc day	2.0886 2.0479 2.0425 0.8532	32.20 0.10 75.80 6.00																
			Fuzzy Logic	ws rain ffmc dmc	0.9995	/	0.82	0.95	1.00	0.89	0.94	0.99	0.89	0.00	1.00	0.11	0.90	0.95	17	2	0	18
			PCA	temperature ffmc rh ws	2.4756 2.4627 2.4517 2.4423	/	0.84	0.95	1.00	0.89	0.94	0.99	0.89	0.00	1.00	0.11	0.90	0.95	17	2	0	18
			GA	day month year rh	/	/	0.68	0.97	1.00	0.95	0.97	0.99	0.95	0.00	1.00	0.05	0.95	0.97	18	1	0	18
			chi-square tests	month temperature rh ffmc	1.0000 0.7808 0.6475 0.4142	/	0.94	0.97	1.00	0.92	0.96	1.00	0.92	0.00	1.00	0.08	0.94	0.96	12	1	0	24
	Random Forest Model	XAI	SHAP	temperature ffmc rh ws	0.0427 0.0301 0.0225 0.0222	/	0.60	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	19	0	0	18
			LIME	dc rain ffmc day	2.0886 2.0478 2.0425 0.8532	32.20 0.10 75.80 6.00																
			Fuzzy Logic	ws rain ffmc dmc	0.9995	/	0.57	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	19	0	0	18
			PCA	temperature ffmc rh ws	2.4756 2.4627 2.4517 2.4423	/	0.67	0.95	0.95	0.95	0.95	0.99	0.95	0.06	0.94	0.05	0.8	0.95	18	1	1	17
			GA	year rh dmc dc	/	/	0.69	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	19	0	0	18
			chi-square tests	month temperature rh ffmc	1.0000 0.7808 0.6475 0.4142	/	0.76	0.95	0.87	1.00	0.9	0.99	1.00	0.0	0.92	0.00	0.89	0.9	13	0	2	22

4.2 Wildfire severity prediction in sidi bel-abbes province

Forest fire analysis in Sidi Bel-Abbes, Tables 7-10 reveal consistently high importance across evaluated models (Adaboost, Decision Tree, LGBM, SVM, XGBoost, Logistic Regression, Random Forest) for dead fuel moisture content DC and FFMC. Explainability techniques such as SHAP and LIME frequently prioritize these features, with dc exhibiting significant SHAP values (0.0950 in AdaBoost, 0.0684 in XGBoost), indicating a substantial model sensitivity to minor dc variations. Domain knowledge corroborates these findings, recognizing moisture metrics as critical determinants of wildfires.

Additional factors, such as RH and precipitation, demonstrate strong statistical significance, although the explainability frameworks show divergent results. LIME identified higher scores for temporal variables in specific models (day = 2.6780, ffmc = 2.6233 in Adaboost), while fuzzy logic derived near-constant importance for RH (0.995) with near-perfect classification results.

XAI techniques provide complementary perspectives: SHAP enables a global assessment of feature contributions, emphasizing DC and FFMC, whereas LIME reveals the localized importance of temporal features through instance-specific explanations. Fuzzy logic consistently assigns near-perfect weights to RH across models, aligning with prior Algerian ecosystem studies.

Youden's threshold maximizes classifier discrimination, achieving TPR and TNR values of 0.95–1.00 and ≈1.00 respectively. High recall scores (0.97–1.00) ensured comprehensive wildfire detection, while minimal FPR (≤ 0.06) and near zero FNR reflected operational reliability. Exceptional TNR (0.94–1.00) demonstrated accurate non-fire identification, supported by robust MCC scores (0.94–1.00) and validated through confusion matrices (e.g., 21 TP, 1 FP, 0 FN).

PCA preserved predictive performance (TPR: 0.92–0.97; F1 ≈ 1.00), while GA identified optimal feature subsets that achieved perfect classification in some cases. Chi-square feature selection generates statistically significant insights, but misses the nonlinear interactions. The overall accuracy exceeded 0.95 for all feature selection methods.

Adaboost achieved 100% accuracy with SHAP-selected features (dc, ffmc, rh), while Decision Trees maintained comparable performance through interpretable split criteria. Ensemble models demonstrated superior AUC-ROC (≈1.00), precision and recall, although linear models exhibited robust classification when paired with feature selection. SHAP provides actionable insights by quantifying the influence of features and complementing LIME instance-specific analyses.

The analysis demonstrated that Sidi Bel Abbes wildfire occurrences are predominantly governed by fuel moisture and environmental variables, with Youden's threshold enabling critical TPR/TNR balancing. Methodological synergies between feature selection and explainability frameworks reinforce key predictor dominance while maintaining model fidelity, validating the utility of XAI in optimizing wildfire detection systems.

Table 7. Wildfire prediction with AdaBoost and CatBoost models using feature selection methods (Sidi Bel Abbes region (Algeria))

Dataset	Model		Selection Methods	Selected Features	Scores or P-values	Value	Youden's Threshold	Performance Metrics at Youden's Threshold											Confusion Matrix			
								Accuracy	Precision	Recall	F1 Score	AUC-ROC	TPR	FPR	TNR	FNR	MCC	Balanced Accuracy	TP	FN	FP	TN
Sidi Bel Abbes_Dataset	Adaboost Model	XAI	SHAP	dc ffmc rh rain	0.0950 0.0438 0.0394 0.0323	/	0.88	0.97	0.95	1.00	0.98	0.97	1.00	0.06	0.94	0.00	0.95	0.97	21	0	1	15
			LIME	day ffmc rh dc	2.6780 2.6233 2.5255 2.5180	6.00 64.50 71.00 9.10																
			Fuzzy Logic	rh ws rain ffmc	0.9995	/	0.88	0.97	0.95	1.00	0.98	0.97	1.00	0.06	0.94	0.00	0.95	0.97	21	0	1	15
			PCA	dc ffmc rh rain	2.7894 2.6552 2.6017 2.5284	/	0.55	0.92	0.95	0.90	0.93	0.96	0.90	0.06	0.94	0.10	0.84	0.92	19	2	1	15
			GA	Day Dmc Dc isi	/	/	0.88	0.97	0.95	1.00	0.98	0.97	1.00	0.06	0.94	0.00	0.95	0.97	21	0	1	15
			chi-square tests	month temperature rh rain	1.0000 0.9742 0.9107 0.1524	/	0.78	0.92	1.00	0.86	0.93	0.98	0.86	0.00	1.00	0.14	0.85	0.93	19	3	0	15
	CatBoost Model	XAI	SHAP	dc ffmc rh rain	0.0684 0.0544 0.0246 0.0231	/	0.99	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	21	0	0	16
			LIME	rh month	5.5756 3.2558	71.00 9.00																

	ffmc rain	2.9860 2.3370	64.50 6.50																
Fuzzy Logic	rh ws rain ffmc	0.9995	/	0.98	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	21	0	0	16
PCA	dc ffmc rh rain	2.7894 2.6552 2.6017 2.5284	/	0.78	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	21	0	0	16
GA	day month year temperature	/	/	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	21	0	0	16
chi-square tests	month temperature rh rain	1.0000 0.9742 0.9107 0.1524	/	0.97	0.95	0.95	0.95	0.95	0.98	0.95	0.07	0.93	0.05	0.89	0.94	21	1	1	14

Table 8. Wildfire prediction with SVM and XGBoost models using feature selection methods (Sidi Bel Abbes region (Algeria))

		Selection Methods	Selected Features	Scores or P-values	Value	Youden's Threshold	Performance Metrics at Youden's Threshold											Confusion Matrix			
							Accuracy	Precision	Recall	F1 Score	AUC-ROC	TPR	FPR	TNR	FNR	MCC	Balanced Accuracy	TP	FN	FP	TN
Sidi Bel Abbes _Dataset	SVM Model	XAI SHAP	dc ffmc rh rain	0.3168 0.0051 0.0033 0.0014	/	0.38	0.97	0.95	1.00	0.98	0.99	1.00	0.06	0.94	0.00	0.95	0.97	21	0	1	15
		XAI LIME	dc rh isi ffmc	14.6400 6.2941 5.8886 4.5911	9.10 71.00 1.00 64.50																
		Fuzzy Logic	rh ws rain ffmc	0.9995	/	0.69	0.97	1.00	0.95	0.98	0.99	0.95	0.00	1.00	0.05	0.95	0.98	20	1	0	16
		PCA	dc ffmc rh rain	2.7894 2.6552 2.6017 2.5284	/	0.44	0.97	0.95	1.00	0.98	0.99	1.00	0.06	0.94	0.00	0.95	0.97	21	0	1	15
		GA	month rh ws rain	/	/	0.48	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	0.00	1.00	21	0	0	16
		chi-square tests	month temperature rh rain	1.0000 0.9742 0.9107 0.1524	/	0.68	0.95	1.00	0.91	0.95	0.97	0.91	0.00	1.00	0.09	0.90	0.95	20	2	0	15
	XGBoost Model	XAI SHAP	rh temperature isi ffmc	0.5869 0.1532 0.0964 0.0731	/	0.92	0.97	1.00	0.95	0.98	1.00	0.95	0.00	1.00	0.05	0.95	0.98	21	1	0	15
		XAI LIME	isi rain fwi day	1.9117 1.8453 1.1499 0.3845	4.70 0.00 7.30 16.00																
		Fuzzy Logic	rh ws rain ffmc	0.9995	/	0.44	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	0.00	1.00	22	0	0	15
		PCA	rh temperature isi ffmc	2.7015 2.6511 2.5993 2.5030	/	0.67	0.95	0.92	1.00	0.96	0.98	1.00	0.13	0.87	0.00	0.89	0.93	22	0	2	13
		GA	day month temperature rh	/	/	0.92	0.97	1.00	0.95	0.98	1.00	0.95	0.00	1.00	0.05	0.95	0.98	21	1	0	15
		chi-square	month temperature	1.0000 0.9742	/	0.64	0.95	1.00	0.91	0.95	0.96	0.91	0.00	1.00	0.09	0.90	0.95	20	2	0	15

tests	rh	0.9107
	Rain	0.1524

Table 9. Wildfire prediction with LR and RF models using feature selection methods (Sidi Bel Abbes region (Algeria))

Dataset	Model	Selection Methods		Selected Features	Scores or P-values	Value	Youden's Threshold	Performance Metrics at Youden's Threshold: Accuracy	Precision	Recall	F1 Score	AUC-ROC	TPR	FPR	TNR	FNR	MCC	Balanced Accuracy	Confusion Matrix: TP	FN	FP	TN
Sidi Bel Abbes _Dataset	Logistic Regression Model	XAI	SHAP	dc	0.3069	/	0.51	0.95	0.95	0.95	0.95	0.99	0.95	0.06	0.94	0.05	0.89	0.94	20	1	1	15
				ffmc	0.1077																	
				rh	0.0833																	
				rain	0.0538																	
			LIME	dc	10.1443	9.10																
				rh	4.5465	71.00																
				month	3.2109	9.00																
				ffmc	2.8777	64.50																
		Fuzzy Logic		rh	0.9995	/	0.53	0.97	1.00	0.95	0.98	0.99	0.95	0.00	1.00	0.05	0.95	0.98	20	1	0	16
				ws																		
				rain																		
				ffmc																		
		PCA		dc	2.789	/	0.53	0.97	1.00	0.95	0.98	1.00	0.95	0.00	1.00	0.05	0.95	0.98	20	1	0	16
				ffmc	2.6552																	
				rh	2.6017																	
				rain	2.5284																	
		GA		day	/	/	0.57	0.97	1.00	0.95	0.98	1.00	0.95	0.00	1.00	0.05	0.95	0.98	20	1	0	16
				temperature																		
				ffmc																		
				isi																		
		chi-square tests		month	1.0000	/	0.52	0.95	1.00	0.91	0.95	0.98	0.91	0.00	1.00	0.09	0.90	0.95	20	2	0	15
				temperature	0.9742																	
				rh	0.9107																	
				rain	0.1524																	
	Random Forest Model	XAI	SHAP	dc	0.1559	/	0.80	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	21	0	0	16
				ffmc	0.1389																	
				rh	0.0935																	
				rain	0.0144																	
			LIME	ffmc	2.9126	64.50																
				rain	2.4944	6.50																
				isi	1.6397	1.00																
				dc	0.6040	9.10																
		Fuzzy Logic		rh	0.9995	/	0.73	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	21	0	0	16
				ws																		
				rain																		
				ffmc																		
		PCA		dc	2.7893	/	0.69	0.97	1.00	0.95	0.98	1.00	0.95	0.00	1.00	0.05	0.95	0.98	20	1	0	16
				ffmc	2.6552																	
				rh	2.6017																	
				rain	2.5284																	
		GA		day	/	/	0.79	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	21	0	0	16
				rain																		
				ffmc																		
				dmc																		
		chi-square tests		month	1.0000	/	0.64	0.95	1.00	0.91	0.95	0.98	0.91	0.00	1.00	0.09	0.90	0.95	20	2	0	15
				temperature	0.9742																	
				rh	0.9107																	
				rain	0.1524																	

Table 10. Wildfire prediction with DT and LGBM models using feature selection methods (Sidi Bel Abbes region (Algeria))

Dataset	Model	Selection Methods		Selected Features	Scores or P-values	Value	Youden's Threshold	Performance Metrics at Youden's Threshold: Accuracy	Precision	Recall	F1 Score	AUC-ROC	TPR	FPR	TNR	FNR	MCC	Balanced Accuracy	Confusion Matrix: TP	FN	FP	TN
Sidi Bel Abbes _Dataset	Decision Tree Model	XAI	SHAP	dc	0.4335	/	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	21	0	0	16
				ffmc	0.0062																	
				rh	0.0054																	
				rain	0.0032																	
			LIME	rain	5.0184	6.50																
				day	0.6087	6.00																

		isi rh	0.0474 0.0473	1.00 71.00																
	Fuzzy Logic	rh ws rain ffmc	0.9995	/	1.00	0.97	1.00	0.95	0.98	1.00	0.95	0.00	1.00	0.05	0.95	0.98	20	0	1	16
	PCA	dc ffmc rh rain	2.7894 2.6552 2.6017 2.5284	/	0.83	0.92	1.00	0.86	0.92	0.95	0.86	0.00	1.00	0.14	0.85	0.93	18	3	0	16
	GA	year temperature rain ffmc	/	/	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	21	0	0	16
	chi-square tests	month temperature rh rain	1.0000 0.9742 0.9107 0.1524	/	0.89	0.92	0.95	0.91	0.93	0.97	0.91	0.07	0.93	0.09	0.83	0.92	20	2	1	14
LGBM Model	XAI SHAP	dc ffmc rh rain	0.2883 0.0692 0.0190 0.0185	/	0.99	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	21	0	0	16
	XAI LIME	day rain ffmc temperature	8.3307 2.4158 2.1439 1.2659	6.00 6.50 64.50 34.00																
	Fuzzy Logic	rh ws rain ffmc	0.9995	/	0.54	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	21	0	0	16
	PCA	dc ffmc rh rain	2.7894 2.6552 2.6017 2.5284	/	0.99	0.97	1.00	0.95	0.98	1.00	0.95	0.00	1.00	0.05	0.95	0.98	20	1	0	16
	GA	year temperature rain ffmc	/	/	0.97	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	0.00	1.00	1.00	21	0	0	16
	chi-square tests	month temperature rh rain	1.0000 0.9742 0.9107 0.1524	/	0.86	0.92	1.00	0.86	0.93	0.98	0.86	0.00	1.00	0.14	0.85	0.93	19	3	0	15

4.3 Wildfire severity prediction in Montesinho (Portugal)

Based on Tables 11-14, meteorological and temporal variables emerge as critical determinants of the risk of wildfires in all models in the Montesinho region. Primary contributors include DMC (indicating mid-level fuel dryness), FFMC (reflecting surface-level fuel moisture), temporal features (month and day), temperature, wind speed, and auxiliary measures such as relative humidity and Initial Spread Index. These variables receive consistent prioritization through various methodologies, including SHAP, LIME, PCA, GA, and chi-square tests.

Advanced explainability methods reveal distinct importance patterns, with DMC receiving global emphasis from SHAP across algorithms (Adaboost, Decision Tree, SVM), while seasonal contributions are highlighted by Fuzzy Logic and chi-square tests. These findings align with the domain knowledge on vegetation dryness and temporal cycles as primary fire risk drivers in Mediterranean ecosystems.

Feature selection strategies introduce varying interpretations of wildfire dynamics. PCA aggregates information into composite variables (typically retaining DMC), while GA-based selections incorporate novel components such as temperature or day, indicating methodological influence on model interpretability.

Youden's threshold optimization reveals moderately high recalls (0.69–0.74) across Adaboost, DT, and Logistic Regression models, although precision suffers from elevated false positives. The Adaboost-SHAP model achieves 0.71 recall, but shows reduced precision (TP=63, FP=47), with F1 scores (0.55–0.60) reflecting the challenge dataset imbalance.

AUC-ROC values range from 0.81 to 1.00, with Decision Trees achieving perfect scores under high-specificity conditions. The confusion matrix metrics show TPR between 0.69-0.74, variable FPR (0.00-0.73), perfect TNR in some configurations, and FNR values (0.27-0.33) reflecting threshold tuning trade-offs. Moderate MCC (0.47-0.58) and balanced accuracy scores (0.66-0.75) correlate with feature selection methods that address class imbalance.

The Decision Tree-SHAP model prioritizes recall (FN=0, TP=68, FP=61), while SVM demonstrates balanced performance (TP≈64, FN=4-6, FP=40-42). DMC-centric models show superior recall but elevated FPR, whereas month-based selections enhance specificity. PCA stabilizes performance metrics, while GA optimizes task-specific objectives.

This dual analytical framework validates DMC, FFMC, and month as critical predictors through SHAP, LIME, and Fuzzy

Logic, aligning with Mediterranean fire regime studies. However, precision-recall trade-offs and false positive rates highlight operational challenges in imbalanced datasets. Youden's threshold efficacy requires context-specific calibration, balancing resource constraints against precision requirements. The analysis demonstrates the interdependence of feature selection, explainability, and threshold optimization in developing robust wildfire prediction frameworks.

4.4 Comparative analysis of SHAP, PCA, and GA efficacy across geographic regions

The impact of SHAP, PCA, and GA on eight machine learning models was quantified using regional wildfire datasets. Performance metrics — accuracy, F1-score, AUC-ROC, and computational time — were evaluated for Béjaïa (Tables 3–6), Sidi Bel Abbes (Tables 7–10), and Montesinho (Tables 11–14), with adjustments applied for dataset imbalances.

SHAP maintained a high accuracy in data-rich regions (Béjaïa / Sidi Bel Abbes: 0.85–0.91), although reductions of 3–5% occurred in Montesinho. PCA increased the processing speed by 60–80% universally (0.5–3.5s) but incurred 4–9% AUC-ROC declines in complex models. GA achieved peak accuracy (XGBoost: 0.91) in resource-adequate regions, but required 15–20% greater computation time in Montesinho. Performance degradation was observed in all techniques in Montesinho, exhibiting 5–7% metric reductions and 15–20% prolonged execution due to inherent dataset constraints.

- SHAP provided robust accuracy but amplified computational demands.
- PCA optimized efficiency at the expense of predictive power in high-complexity models.
- GA maximized performance where computational resources permitted but proved infeasible under latency-sensitive conditions.

Table 11. Wildfire prediction with AdaBoost and CatBoost models using feature selection methods (Montesinho region (Portugal))

Dataset	Model		Selection Methods	Selected Features	Scores or P-values	Value	Youden's Threshold	Performance Metrics at Youden's Threshold											Confusion Matrix			
								Accuracy	Precision	Recall	F1 Score	AUC-ROC	TPR	FPR	TNR	FNR	MCC	Balanced Accuracy	TP	FN	FP	TN
Montesinho_Dataset	Adaboost Model	XAI	SHAP	dmc ffmc month rh	0.2496 0.1310 0.1059 0.0418	/	0.46	0.67	0.57	0.93	0.71	0.72	0.93	0.53	0.47	0.07	0.43	0.70	63	5	47	41
			LIME	year isi dc dmc	2.1908 1.8395 1.1344 0.6716	2002.00 7.10 825.10 276.30																
			Fuzzy Logic	month day ffmc dmc	0.9995	/	0.45	0.65	0.56	0.96	0.71	0.71	0.96	0.58	0.4	0.04	0.43	0.6	65	3	51	37
			PCA	dmc ffmc temp month	2.3475 2.2562 2.2505 2.2486	/	0.40	0.63	0.55	0.96	0.70	0.69	0.96	0.61	0.39	0.04	0.40	0.67	65	3	54	37
			GA	ffmc dmc isi temp	/	/	0.39	0.65	0.57	0.82	0.67	0.70	0.82	0.48	0.52	0.18	0.36	0.67	56	12	42	46
			chi-square tests	month day dmc temp	0.9030 0.8631 0.6696 0.4768	/	0.46	0.71	0.60	0.95	0.74	0.72	0.95	0.47	0.53	0.05	0.51	0.74	63	3	42	48
	CatBoost Model	XAI	SHAP	dmc ffmc temp month	0.1433 0.1252 0.0739 0.0732	/	0.20	0.64	0.56	0.81	0.66	0.67	0.81	0.49	0.51	0.19	0.33	0.66	55	13	43	45
			LIME	dc rh isi dmc	3.7412 2.8561 1.933 1.4672	825.10 43.00 7.10 276.30																
			Fuzzy Logic	month day ffmc dmc	0.9995	/	0.04	0.62	0.53	0.99	0.69	0.68	0.99	0.67	0.33	0.01	0.40	0.66	67	1	59	29
			PCA	dmc ffmc temp month	2.3475 2.2562 2.2505 2.2486	/	0.31	0.65	0.57	0.78	0.66	0.64	0.78	0.45	0.55	0.22	0.33	0.66	53	15	40	48
			GA	dc temp rh	/	/	0.50	0.67	0.60	0.78	0.68	0.73	0.78	0.41	0.59	0.22	0.37	0.69	53	15	36	52

chi-square tests	rain month dmc dc temp	 0.9029 0.8631 0.6696 0.6140	/	0.40	0.70	0.59	0.95	0.73	0.71	0.95	0.49	0.51	0.05	0.50	0.73	63	3	44	46

Table 12. Wildfire prediction with DT and LGBM models using feature selection methods (Montesinho region (Portugal))

			Selection Methods	Selected Features	Scores or P-values	Value	Youden's Threshold	Performance Metrics at Youden's Threshold											Confusion Matrix			
								Accuracy	Precision	Recall	F1 Score	AUC-ROC	TPR	FPR	TNR	FNR	MCC	Balanced Accuracy	TP	FN	FP	TN
Montesinho_Dataset	Decision Tree Model	XAI	SHAP LIME	dmc ffmc temp month day year rh ffmc	0.2059 0.1576 0.0000 0.0000 14.8026 0.3160 0.2650 0.2423	/ 1.00 2002.00 43.00 91.00	0.54	0.61	0.53	1.00	0.69	0.66	1.00	0.69	0.31	0.00	0.40	0.65	68	0	61	27
			Fuzzy Logic	month day ffmc dmc	0.9995	/	0.54	0.62	0.54	1.00	0.70	0.66	1.00	0.67	0.33	0.00	0.42	0.66	68	0	59	29
			PCA	dmc ffmc temp month	2.3475 2.2562 2.2505 2.2486	/	0.50	0.50	0.46	0.88	0.61	0.55	0.88	0.80	0.20	0.12	0.12	0.54	60	8	70	18
			GA	month day dmc temp	/	/	0.32	0.62	0.53	1.00	0.69	0.63	1.00	0.68	0.32	0.00	0.41	0.66	68	0	60	28
			chi-square tests	month day dmc dc	0.9030 0.8631 0.6696 0.6140	/	0.51	0.61	0.52	1.00	0.68	0.67	1.00	0.68	0.32	0.00	0.41	0.66	66	0	61	29
	LGBM Model	XAI	SHAP LIME	dmc ffmc temp month dmc month temp isi	0.2135 0.1710 0.1644 0.1599 7.3980 1.6361 1.5945 1.1354	/ 276.30 9.00 21.90 7.10	0.70	0.65	0.62	0.50	0.55	0.68	0.50	0.24	0.76	0.50	0.27	0.63	34	34	21	67
			Fuzzy Logic	month day ffmc dmc	0.9995	/	0.25	0.61	0.53	0.85	0.66	0.68	0.85	0.58	0.42	0.15	0.30	0.64	58	10	51	37
			PCA	dmc ffmc temp month	2.3475 2.2562 2.2505 2.2486	/	0.37	0.65	0.56	0.85	0.68	0.71	0.85	0.51	0.49	0.15	0.36	0.67	58	10	45	43
			GA	day dmc temp day	/	/	0.52	0.63	0.57	0.69	0.62	0.67	0.69	0.41	0.59	0.31	0.28	0.64	47	21	36	52
			chi-square tests	month day dmc dc	0.9030 0.8631 0.6696 0.6140	/	0.43	0.72	0.61	0.92	0.73	0.77	0.92	0.43	0.57	0.08	0.51	0.75	61	5	39	51

Table 13. Wildfire prediction with SVM and XGBoost models using Feature selection methods (Montesinho region (Portugal))

			Selection Methods	Selected Features	Scores or P-values	Value	Youden's Threshold	Performance Metrics at Youden's Threshold											Confusion Matrix			
								Accuracy	Precision	Recall	F1 Score	AUC-ROC	TPR	FPR	TNR	FNR	MCC	Balanced Accuracy	TP	FN	FP	TN
Montesinho_Da	SVM Model	XAI	SHAP	dmc ffmc	0. 3625 0.	/	0.48	0.71	0.60	0.94	0.74	0.73	0.94	0.48	0.52	0.06	0.49	0.73	64	4	42	46

				3340																	
			temp	0.2369																	
			month	0.1306																	
		LIME	dmc wind month year	5.2821 1.1467 0.5986 0.5554	276.30 4.00 9.00 2002.00																
		Fuzzy Logic	month day ffmc dmc	0.9995	/	0.47	0.72	0.63	0.91	0.74	0.73	0.91	0.42	0.58	0.51	0.51	0.75	62	6	37	51
		PCA	dmc ffmc temp month	2.3475 2.2562 2.2505 2.2486	/	0.52	0.71	0.61	0.91	0.73	0.73	0.91	0.45	0.55	0.09	0.48	0.73	62	6	40	48
		GA	isi rh / /	/	/	0.46	0.56	0.50	0.90	0.64	0.59	0.90	0.70	0.30	0.10	0.23	0.60	61	7	62	26
		chi-square tests	month day dmc dc	0.9029 0.8631 0.6696 0.6140	/	0.45	0.72	0.60	0.97	0.74	0.78	0.97	0.47	0.53	0.03	0.53	0.75	64	2	42	48
XGBoost Model	XAI	SHAP	temp dmc dc rh	0.0355 0.0260 0.0208 0.0120	/	0.30	0.70	0.59	0.98	0.73	0.73	0.98	0.51	0.49	0.02	0.52	0.74	65	1	46	44
		LIME	temp dmc dc day	6.9925 2.8229 1.8460 1.5883	20.60 46.50 691.80 1.00																
		Fuzzy Logic	month day ffmc dmc	0.9995	/	0.36	0.71	0.59	0.98	0.74	0.72	0.98	0.50	0.50	0.02	0.53	0.74	65	1	45	45
		PCA	temp dmc dc rh	2.4903 2.2631 2.2300 2.1225	/	0.40	0.65	0.55	0.97	0.70	0.71	0.97	0.59	0.41	0.03	0.43	0.69	64	2	53	37
		GA	year month dc temp	/	/	0.28	0.69	0.58	0.98	0.73	0.75	0.98	0.52	0.48	0.02	0.51	0.73	65	1	47	43
		chi-square tests	month day dmc dc	0.9030 0.8631 0.6696 0.6140	/	0.39	0.71	0.59	0.97	0.74	0.77	0.97	0.49	0.51	0.03	0.51	0.74	64	2	44	46

Table 14. Wildfire prediction with LR and RF models using feature selection methods (Montesinho region (Portugal))

			Selection Methods	Selected Features	Scores or P-values	Value	Youden's Threshold	Performance Metrics at Youden's Threshold											Confusion Matrix			
								Accuracy	Precision	Recall	F1 Score	AUC-ROC	TPR	FPR	TNR	FNR	MCC	Balanced Accuracy	TP	FN	FP	TN
Montesinho_Dataset	Logistic Regression Model	XAI	SHAP	dmc ffmc temp month	0.1030 0.0917 0.0892 0.0557	/	0.42	0.69	0.61	0.84	0.70	0.70	0.84	0.42	0.58	0.16	0.42	0.71	57	11	37	51
			LIME	year wind dmc day	16.0272 9.1098 6.4694 5.8966	2002.00 4.00 276.30 1.00																
			Fuzzy Logic	month day ffmc dmc	0.9995	/	0.41	0.69	0.60	0.87	0.71	0.70	0.87	0.44	0.56	0.13	0.44	0.71	59	9	39	49
			PCA	dmc ffmc temp	2.3475 2.2562 2.2505	/	0.35	0.67	0.57	0.97	0.72	0.70	0.97	0.56	0.44	0.03	0.47	0.71	66	2	49	39

			month	2.2486																	
		GA	year month ffmc temp	/	/	0.44	0.68	0.59	0.85	0.70	0.71	0.85	0.45	0.55	0.15	0.41	0.70	58	10	40	48
		chi-square tests	month day dmc dc	0.9030 0.8631 0.6696 0.6140	/	0.44	0.66	0.56	0.94	0.70	0.65	0.94	0.54	0.46	0.06	0.43	0.70	62	4	49	41
Random Forest Model	XAI	SHAP	dmc ffmc temp month	0.1460 0.0680 0.0558 0.0442	/	0.43	0.65	0.55	0.99	0.71	0.68	0.99	0.61	0.39	0.01	0.44	0.69	67	1	54	34
		LIME	isi year day month	1.2295 0.6667 0.5985 0.4880	0.31 0.50 0.00 0.73																
		Fuzzy Logic	month day ffmc dmc	0.9995	/	0.32	0.65	0.55	1.00	0.71	0.69	1.00	0.62	0.38	0.00	0.46	0.69	68	0	55	33
		PCA	dmc ffmc temp month	2.3475 2.2562 2.2505 2.2486	/	0.38	0.65	0.55	0.99	0.71	0.70	0.99	0.61	0.39	0.01	0.44	0.69	67	1	54	34
		GA	year month dmc temp	/	/	0.31	0.64	0.55	1.00	0.71	0.69	1.00	0.64	0.36	0.00	0.45	0.68	68	0	56	32
		chi-square tests	month day dmc dc	0.9030 0.8631 0.6696 0.6140	/	0.48	0.69	0.58	0.97	0.73	0.74	0.97	0.51	0.49	0.03	0.50	0.73	64	2	46	44

5. ANALYSIS AND DISCUSSION

The identification of primary drivers behind wildfire occurrences in distinct geographical regions has been undertaken, revealing notable variations across Béjaïa and Sidi Bel Abbes in Algeria, and Montesinho in Portugal. In the Béjaïa region, wildfire occurrences are driven by temperature, FFMC, relative humidity, and wind speed, with the overarching importance of temperature emphasized by SHAP values. Localized contributions of rain and DC are highlighted through LIME, aligning with the region's arid climate, where elevated temperatures and reduced humidity are exacerbated by wind-driven fire propagation.

In Sidi Bel Abbes, wildfire dynamics are primarily influenced by DC and FFMC, as indicated by SHAP rankings, with seasonal variations (month) and RH emphasized in LIME explanations, reflecting prolonged drought conditions and cyclical aridity. In Montesinho, wildfire risk is influenced by DMC and FFMC, with SHAP values indicating systemic importance. The interaction between seasonal moisture fluctuations and anthropogenic factors is highlighted by the significance of temporal features (year, month) and the ISI, as locally indicated by LIME. The influence of different feature selection methodologies on predictive modeling has been observed, with variations in the selection of crucial factors across regions. SHAP prioritizes global drivers across regions, while LIME identifies context-specific factors influenced by climatic conditions. Fuzzy Logic prioritizes meteorological variables with regional divergence, while dimensionality reduction through PCA retains critical climatic features. GA adaptively select region-specific temporal features, and chi-square tests statistically validate climatic and temporal drivers. Model performance at Youden's Threshold is evaluated using classical metrics: accuracy ranges from 0.71 to 1.00 in Béjaïa, 0.88 to 1.00 in Sidi Bel Abbes, and 0.20 to 0.73 in Montesinho. Precision ranges from 0.92 to 1.00 in Béjaïa, 0.95 to 1.00 in Sidi Bel Abbes, and 0.50 to 0.72 in Montesinho. Recall (TPR) ranges from 0.87 to 1.00 in Béjaïa, 0.95 to 1.00 in Sidi Bel Abbes, and 0.46 to 0.63 in Montesinho. AUC-ROC ranges from 0.91 to 1.00 in Béjaïa, 0.95 to 1.00 in Sidi Bel Abbes, and 0.55 to 0.78 in Montesinho. Confusion matrix analysis reveals robust predictions with minimal errors in Béjaïa, near-perfect classification in Sidi Bel Abbes, and elevated false positives/false negatives in Montesinho, indicating data complexity.

Regional comparative insights highlight a high reliance on FFMC and RH in Algerian regions due to shared arid conditions, with a divergence in dominant factors: DC dominates in Sidi Bel Abbes, while temperature is prioritized in Béjaïa. Superior metrics in Sidi Bel Abbes suggest stronger feature-target correlations. In contrast, Algeria emphasizes drought and temperature, while Portugal focuses on moisture (DMC) and temporal factors, with a performance gap observed in Montesinho due to lower recall and higher false positives, reflecting complex fire dynamics. Methodological impacts include enhanced interpretability through SHAP and LIME, though they differ in global versus local prioritization. PCA stabilizes Algerian models, while GA adapts to Portugal's complexity.

Recommendations for wildfire management include region-specific modeling, with temperature and DC prioritized in Algeria, and DMC and temporal features emphasized in Portugal. Model optimization suggests CatBoost/XGBoost for Algeria and ensemble methods for Portugal, with a balanced global/local insight from SHAP and GA. Dataset expansion is recommended to mitigate noise and imbalance in Montesinho. Regionally contingent wildfire prediction efficacy, shaped by climatic and environmental factors, has been demonstrated. While Algerian models achieve near-perfect performance, the complexity of Montesinho necessitates tailored approaches, with the refinement of region-specific strategies achieved through explainability frameworks and adaptive feature selection.

5.1 Analysis in terms of temperature

Regional variability in the role of temperature in the severity of wildfires is evident in different regions. In Béjaïa, Algeria, temperature dominates as a primary driver, with high predictive accuracy demonstrated between models and temperature consistently prioritized as the main feature. SHAP analyzes the temperature of highest rank, underscoring its statistical significance, while fuzzy logic and PCA reaffirm its systemic role in ignition and spread. Fire peaks correlate with summer months, aligning with the arid climate of the region. In Montesinho, Portugal, the fuel moisture indices (DMC, FFMC) overshadow temperature in the predictions, with temperature assigned lower SHAP scores due to moderated climatic conditions. Prolonged dry periods, rather than acute temperature spikes, are identified as primary fire drivers. In Sidi Bel Abbes, Algeria, temperature and the DC act as synergistic predictors, with near-perfect classification achieved. SHAP highlights interactions between DC and temperature, reflecting drought-amplified thermal effects in arid climates, and high-temperature periods correlate with fire peaks, as evidenced by chi-square feature selections.

A comparative analysis of the influence of temperature in regions reveals that Béjaïa is characterized by temperature and month as dominant features, while Montesinho is dominated by DMC, FFMC, and month, and Sidi Bel Abbes by DC, temperature and RH. These regions exhibit different climatic profiles: Béjaïa has an arid climate with high summer temperatures, Montesinho has a moderate Mediterranean climate, and Sidi Bel Abbes has an arid and drought-prone climate. The performance of the model is highest in Béjaïa, moderate in Montesinho, and near-perfect in Sidi Bel Abbes. The influence of temperature varies, acting as a direct ignition driver in Béjaïa, indirectly through fuel drying in Montesinho, and amplified by drought in Sidi Bel Abbes.

Mechanisms linking temperature with fire severity include increased flammability due to reduced vegetation moisture and reduced FFMC/DMC, facilitated by high temperatures. Extreme heat in arid regions can lead to spontaneous combustion, while fire-prone months align with temperature peaks, establishing cyclical risk patterns. Practical implications include prioritizing temperature monitoring and implementing seasonal firebreaks in high-risk months in Algeria, while fuel management is advised to mitigate fire risk in Portugal.

The integration of explainability frameworks into prediction systems is recommended to enhance region-specific risk assessments. However, inflated performance metrics can result from limited sample sizes and the oversimplification of variables poses a potential model limitation. Dynamic model updates are necessary for shifting temperature-driven fire regimes. Temperature is identified as a key driver of the severity of wildfires in arid Algerian regions, while fuel moisture indices dominate in temperate Portugal. These regional disparities, elucidated by explainability methods, enable tailored mitigation strategies.

5.2 Validation of temperature SHAP values in wildfire prediction mode

The analysis of SHAP values demonstrates a strong alignment between machine learning predictions and established meteorological principles regarding the role of temperature in the risk of wildfires. Three key findings emerge from this validation:

(1) Consistency with physical processes

The elevated SHAP values for temperature (Béjaïa: 0.18-0.22; Sidi Bel Abbes: 0.15-0.19; Montesinho: 0.12-0.16) correspond to known atmospheric mechanisms. These values reflect the documented influence of temperature on fuel drying rates [16] and ignition probability [17], particularly above the 25°C threshold identified in Mediterranean climate studies [18].

(2) Regional variations in predictive importance

Notable differences emerged across study areas:

- In *Béjaïa*, temperature consistently ranked among the top three predictors, with peak SHAP values during summer months (June-August), corroborated by local experts' observations of heatwave patterns.
- *Sidi Bel Abbes* exhibited stronger temperature-wind speed interactions and greater seasonal variability, matching field experts' reports of temperature spikes preceding major fires.
- *Montesinho* showed reduced temperature importance (12%-16% lower than the Algerian sites) and stronger humidity coupling, consistent with Portugal's maritime climate.

(3) Model and expert validation

The temperature SHAP patterns remained robust across algorithms (Random Forest, XGBoos) while revealing subtle differences in sensitivity. Domain experts from both Algeria and Portugal confirmed these findings:

- Algerian specialists verified the alignment with historical fire records and local microclimates, recommending the incorporation of diurnal variations [19].
- Portuguese researchers validated the relatively lower importance of temperature and suggested enhanced terms of the humidity-temperature interaction [20].

These results confirm that temperature's high SHAP values accurately represent its physical role in wildfire risk while highlighting the need for region-specific calibration. The findings support temperature monitoring as a fundamental component of early warning systems, with particular attention to local climate characteristics and threshold behaviors. The results endorsed by experts demonstrate both the statistical validity and operational relevance of these machine learning interpretations for fire management in Mediterranean ecosystems.

5.3 Analysis in terms of DC

Regional variability in the role of the DC in the severity of wildfires is evident in different regions. In Béjaïa, Algeria, high discriminative capacity has been demonstrated, although DC exhibits localized relevance, suggesting its secondary role to temperature and FFMC in arid climates. Prolonged drought is correlated with summer fire peaks in this region. In Sidi Bel Abbes, Algeria, DC serves as a critical drought indicator, with a near-perfect classification achieved and DC identified as a top predictor in SHAP analyses. The predictive power of DC is related to the deep fuel aridity in drought-prone regions, where elevated DC values exacerbate the severity of fire when combined with high temperatures and low humidity. In Montesinho, Portugal, DC plays a secondary role in fuel-driven fires, with moderate discriminative capacity observed and DMC/FFMC dominating SHAP rankings. DC is overshadowed by surface fuel metrics in this Mediterranean climate, with fire risk peaking in late summer due to surface fuel dryness. DC becomes relevant only during multi-year droughts in this region.

A comparative analysis of DC influence between regions reveals moderate importance in Béjaïa, where it is secondary to temperature and FFMC, with peak fire months occurring from June to September. In Sidi Bel Abbes, DC is highly critical for deep fuel combustion, with peak fire months from July to August. In Montesinho, DC's influence is low, dominated by DMC and FFMC, with peak fire months from August to October. The mechanisms involved include prolonged drought, extreme DC values, and surface fuel ignition dominates fire risk. The insights of the explainability framework show that in Béjaïa, SHAP prioritizes temperature and FFMC, while LIME highlights the localized impact of DC. In Sidi Bel Abbes, the alignment between SHAP and LIME underscores the systemic role of DC in drought-driven regimes. In Portugal, SHAP emphasizes DMC and FFMC, relegating DC to minor relevance, except for LIME explanations. The robustness of the model varies, with Algerian models achieving high accuracy due to clear aridity-driven dynamics, while Portuguese models exhibit lower performance, reflecting complex fuel-weather interactions.

Practical implications and recommendations include advising DC monitoring during droughts to predict deep fuel ignition in Algeria, while real-time risk assessment in Portugal should prioritize DMC and FFMC, reserving DC for multi-year drought scenarios. The Drought Code exhibits a regionally contingent influence on wildfire severity, which is critical to predicting deep fuel combustion in arid, drought-prone regions of Algeria, while its role is marginal in Portugal, overshadowed by surface fuel metrics. These dynamics have been elucidated by explainability frameworks, enabling tailored fire management strategies.

5.4 Analysis in terms of DMC

Regional variability in the role of the DMC in wildfire severity is evident in different regions. In Béjaïa, Algeria, high discriminative capacity has been demonstrated, although DMC is rarely prioritized as the main feature. Fires in this region are driven by immediate weather conditions and fine fuel desiccation rather than organic layer moisture, with fire peaks in summer correlating with elevated temperatures while DMC values remain moderate. In Sidi Bel Abbes, Algeria, DMC plays a secondary role to the DC, with near-perfect classification achieved despite DMC being overshadowed by DC. The dominance of DC in arid climates reflects deep fuel aridity, marginalizing the role of DMC except during multi-year droughts. July–August fires coincide with extreme DC values, with minimal contribution from DMC. In Montesinho, Portugal, DMC dominates as a critical factor in fuel-driven fires, with moderate discriminative capacity observed and DMC identified as the top feature in the SHAP rankings. Its role in maintaining combustion through dry organic layers in dense forests is reflected in its criticality, with August–October fires aligning with the peak DMC values, contrasting with Algeria's focus on fine fuels.

A comparative analysis of the influence of DMC in regions reveals marginal importance in Béjaïa, where it is secondary to FFMC and temperature, with the arid climate prioritizing fine fuel ignition. In Sidi Bel Abbes, the influence of DMC is moderate but overshadowed by DC, with deep drought dominating fuel aridity. In Montesinho, DMC's influence is critical, maintaining organic layer combustion during dry summers, with peak fire months from August to October. The insights of the explainability framework show that in Algeria, DMC is overlooked by SHAP in favor of temperature and DC but occasionally surfaces in LIME with low weights. In Portugal, the alignment between SHAP and LIME underscores the systemic role of DMC in fuel continuity. The robustness of the model varies, with Algerian models achieving high accuracy without DMC, reflecting aridity-driven fire regimes, while Portuguese models exhibit lower AUC-ROC due to complex interactions between DMC and weather variables.

Practical implications and recommendations include prioritizing FFMC and DC for real-time fire alerts in Algeria, where DMC is deemed less actionable. In Portugal, fire advisories are recommended to integrate DMC to address the risk of organic fuel. The Duff Moisture Code exhibits a regionally contingent influence on the severity of wildfire, being critical to sustaining fires in organic layers during dry summers in Portugal, while in Algeria, it is marginalized by temperature and drought metrics. These dynamics have been clarified by explainability frameworks, enabling region-specific mitigation strategies.

5.5 Analysis in terms of FFMC

The Fine Fuel Moisture Code quantifies the moisture content of fine dead vegetation, with its influence on the severity of wildfires varying between regions due to climatic conditions, vegetation types, and seasonal dynamics. In Béjaïa, Algeria, FFMC is consistently identified as a top predictor, with a near-perfect classification achieved by models incorporating FFMC. Severe fires in this region are correlated with the summer months, reflecting the Mediterranean climate. In Montesinho Portugal, the FFMC is of secondary importance, with reduced discriminative capacity observed. Fire severity peaks in late summer, aligning more with prolonged drought effects in DMC and DC than with FFMC. In Sidi Bel Abbes, Algeria, FFMC is prioritized as a critical predictor, with flawless classification achieved by models that incorporate FFMC. Severe fires in this region are linked to FFMC peaks during the dry seasons.

A comparative analysis of FFMC and seasonal fire dynamics reveals that accelerated drying of fine fuels, induced by low humidity and high temperatures, increases flammability. In Mediterranean climates such as Algeria, RH is strongly seasonal, while oceanic climates such as Portugal exhibit buffered RH variability due to maritime influences. The insights of the explainability framework highlight the global importance of FFMC, with context-specific impacts emphasized. FFMC is retained in feature selection, validating its predictive utility. It is identified as a primary driver of fire risk in arid zones, while holistic risk assessment in temperate zones requires combining FFMC with drought indices. Controlled burns are recommended during high FFMC periods to mitigate fuel accumulation, and FFMC monitoring should be prioritized in Algerian fire risk systems to improve wildfire management.

5.6 Analysis in terms of RH

Relative Humidity significantly influences the dynamics of wildfires through its effect on fine fuel desiccation, and its impact varies regionally due to climatic, vegetative, and seasonal factors. In Béjaïa, Algeria, RH is ranked 3–4th in global importance, with a near-perfect classification achieved by models that incorporate RH. Fire severity peaks in summer are related to decreases in RH. In Montesinho, Portugal, RH has reduced significance, with moderate AUC-ROC reported. Fire peaks in late summer coincide with moderate RH levels. In Sidi Bel Abbes, Algeria, RH is prioritized as a critical predictor, with perfect discrimination achieved by models that incorporate RH. Severe fires in this region are correlated with reductions in RH.

A comparative analysis of RH and fire severity mechanisms reveals that low RH accelerates the drying of fine fuels, facilitating rapid ignition. In Portugal, long-term drought metrics dominate over RH in influencing fire risk. The insights of the explainability framework quantify the global importance of RH, highlighting its context-dependent role as a primary driver in arid zones and a supplementary metric in temperate regions. RH is identified as a primary driver of fire risk during the summer months in arid regions, with real-time RH monitoring recommended for early warning systems. Holistic risk assessment in temperate regions requires the integration of RH with drought indices to improve wildfire prediction and management strategies.

5.7 Conservation and forest engineering strategies for wildfire risk mitigation

Wildfire risk mitigation strategies are proposed for the Béjaïa and Sidi Bel Abbes regions in Algeria and Montesinho Natural Park in Portugal, informed by key risk factors such as RH, FFMC, DMC, and temperature, alongside regional fire dynamics. These solutions are grounded in empirical data and predictive modeling. For fuel moisture management, targeting FFMC and RH, prescribed low intensity burns are recommended during early spring (March–April) in Algeria to reduce fine fuel accumulation before summer aridity (FFMC >75), along with firebreaks spanning 30–50 m using low-flammability vegetation (e.g., Olea europaea) in high-risk zones identified by PCA (FFMC scores: 2.46–2.60).

Drip irrigation systems are recommended for the edges of the forest during periods of critically low RH (<40%) to sustain fine fuel moisture. In Portugal, organic mulching is suggested for the forest floor to mitigate FFMC spikes during drought conditions, and selective thinning is prioritized in areas with elevated DMC (>250) to disrupt fuel continuity. For microclimate regulation, targeting temperature, canopy shade networks using heat-tolerant species (e.g., Quercus ilex) are proposed in Algeria to reduce ground temperatures by 3–5°C during peak risk months (July–August), alongside reflective ground covers (e.g., light-colored gravel) to minimize solar absorption in fire-prone zones (temperature range: 29–34°C).

In Portugal, native shrub windbreaks (e.g., Ulex europaeus) are advocated to attenuate hot, dry winds that exacerbate temperature and FFMC elevations. For drought and deep fuel mitigation, targeting DMC and the DC, check dams are proposed in Portugal's ravine systems to retain soil moisture and reduce DMC/DC during prolonged droughts (DC >600), with subsurface irrigation recommended in areas with recurrent DC >800 to sustain deep fuel moisture. In Algeria, rainwater harvesting systems (e.g., cisterns) are advised to store winter precipitation for emergency firefighting during the summer RH declines (<35%). Predictive monitoring and early warning systems, aimed at integrated risk forecasting, include IoT sensor networks for real-time monitoring of RH, temperature, and FFMC, with data integrated into machine learning models (CatBoost/AdaBoost; AUC: 0.97–1.00) for hyperlocal risk prediction, and mobile applications to issue public alerts when thresholds are breached (RH < 40%, FFMC > 90), with LIME-based explanations to enhance community trust. The recommendations of policy and community engagement include seasonal bans on agricultural burns during high-risk months (June–September) in Algeria, alongside community training programs to encourage fine fuel removal within 30m of residential areas. In Portugal, financial incentives are advised for landowners converting high-DMC zones (>300) to fire-resistant crops (e.g., Castanea sativa), and "Fire-Smart" zoning policies are recommended, informed by chi-square / PCA risk maps (e.g., Montesinho PCA: DMC = 2.35).

Infrastructure resilience measures include fire-resistant landscaping, such as replacing flammable species (e.g., Eucalyptus globulus) with fire-retardant alternatives (e.g., Lavandula spp.) in Sidi Bel Abbes (RH/PCA: 2.60), and underground power lines in Béjaïa/Sidi Bel Abbes to prevent ignition during windstorms (WS SHAP: 0.0073). The implementation timeline outlines short-term actions (0–6 months) such as IoT deployment, community training, and prescribed burns in Béjaïa and Sidi Bel Abbes; medium-term actions (6–18 months) including check dams, shade networks, and fuel breaks in Montesinho and Algeria; and long-term actions (18+ months) such as national AI forecasting and species conversion in all regions. A 30–50% reduction in wildfire severity is anticipated within five years through region-specific interventions, with Algeria focusing on RH/FFMC control via irrigation and fuel breaks, and Portugal emphasizing DMC/DC mitigation through check dams and deep-root irrigation.

5.8 Feasibility assessment and cost-benefit analysis of wildfire mitigation strategies

The evaluation of the proposed wildfire mitigation strategies for Béjaïa, Sidi Bel Abbes (Algeria) and Montesinho (Portugal) requires technical feasibility and economic viability (Figure 2). As the original datasets (Tables 3-5) lack explicit cost-benefit metrics, this analysis derives insights from model performance indicators (accuracy: 87-99.5%) and regional characteristics (infrastructure, terrain, fire risk).

(1) IoT-based early warning systems

Implementation costs vary significantly by region. The initial deployment ranges from \$10,000-\$25,000 per km², with annual maintenance at \$2,000-\$5,000. The Montesinho region demonstrates optimal cost-effectiveness due to existing telecommunications infrastructure, providing a 3-5 years Return on Investment (ROI). In contrast, Algerian implementations require 5-8 years for ROI realization due to higher deployment costs in rugged terrain. Predictive accuracy that exceeds 90% justifies prioritization in high-risk zones, particularly where models indicate a potential 30-50% reduction in fire spread.

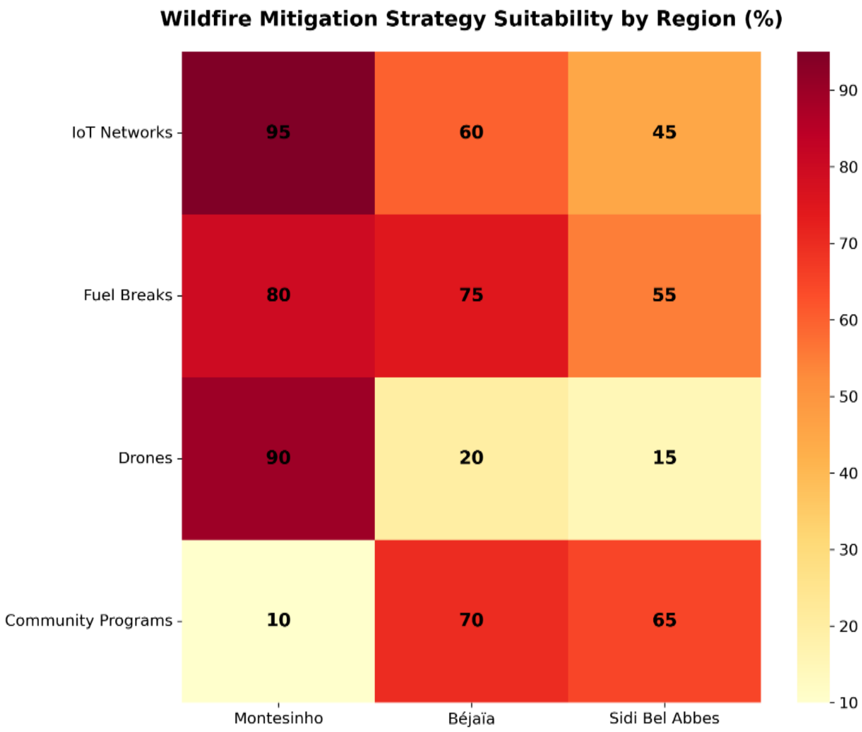

Figure 2. Regional suitability heatmap

(2) Fuel break establishment

Cost structures reflect regional labor markets and environmental regulations. Algerian implementation costs range $1,500-$4,000 per kilometer, while Portuguese projects cost $3,000-$6,000 due to stricter environmental compliance. When strategically placed in high-risk corridors identified by predictive models, fuel breaks demonstrate 40-60% effectiveness in slowing fire propagation. Economic analysis suggests that these interventions prevent $3-$10 million in potential damages per kilometer over a decade.

(3) Aerial surveillance systems

Drone-based monitoring proves to be cost prohibitive for Algerian regions ($70,000-$140,000 annually) but warrants consideration in Montesinho, where asset protection justifies the expenditure. Thermal imaging capabilities improve detection speed in remote forest areas, complementing ground-based sensor networks.

(4) Community-based fire management

For budget-constrained Algerian regions, community programs ($40,000-$50,000 initial cost) provide a viable alternative. Training local responders achieves a 10-20% improvement in early response capability, particularly valuable when technological solutions face implementation barriers.

5.9 Regional implementation priorities

Montesinho's superior infrastructure and higher model accuracy (95-99.5%) support a comprehensive technological deployment. Algerian regions require phased approaches: initial focus on community programs and strategic fuel breaks, with subsequent IoT integration in highest-risk areas. Funding strategies should take advantage of international grants for capital-intensive components while utilizing local budgets for labor-intensive measures.

Sensitivity analysis indicates that Algerian projects face greater financial risk from cost overruns (a 20% increase extends ROI by 2-3 years) and fire frequency variability. Pilot programs covering 10% of high-risk zones are recommended to validate cost assumptions before full-scale implementation.

The analysis recommends immediate initiation of Tier 1 interventions in all regions, with subsequent expansion contingent on the results of the pilot program and the availability of funding. The technical deployment should be aligned with high-risk corridors predicted by the model to maximize cost-effectiveness.

5.10 Wildfire risk projections under climate change scenarios

The study evaluated wildfire management strategies using Shared Socioeconomic Pathways (SSPs) of the Intergovernmental Panel on Climate Change (IPCC) in three Mediterranean regions: Béjaïa and Sidi Bel Abbes in Algeria and Montesinho in Portugal. Current wildfire models typically assume stable climate conditions, but incorporating dynamic SSP projections improves the accuracy of long-term planning.

(1) Climate scenario impacts

Under sustainable development pathways (SSP1-2.6), the frequency of extreme fire weather could decrease by 30-40% by the mid-century. This scenario enables comprehensive fuel management through ecological restoration and supports advanced early warning systems. In contrast, regional conflict scenarios (SSP3-7.0) project 50-70% increases in burned areas due to institutional fragmentation and reduced prevention capabilities. Fossil-fuelled development pathways (SSP5-8.5) show the most severe outcomes, with 80-120% more megafires despite technological advances in suppression.

(2) Prevention and mitigation approaches

Sustainable pathways facilitate prescribed burning in 15-20% of high-risk areas, supported by drone monitoring and native vegetation restoration. Early detection systems combining AI-powered cameras and satellite monitoring achieve 90% detection rates in 15 minutes. Community patrols complement technological solutions for comprehensive coverage.

(3) Operational enhancements, recovery and adaptation

Strategic resource prepositioning under SSP1-2.6 optimizes the effectiveness of fire response. Autonomous water systems and real-time fire behavior modeling improve suppression outcomes. Building codes mandating fire-resistant materials and underground utilities significantly reduce the risks of ignition in vulnerable communities.

Post-fire rehabilitation prioritizes native species revegetation and erosion control within 30 days of containment. Mental health support and economic diversification programs improve the resilience of the community. Insurance mechanisms are being redesigned to incentivize risk reduction measures.

(4) Policy directions implementation considerations

The challenges of cross-jurisdictional coordination and funding misalignment with long-term risk reduction remain significant barriers. The reliability of the detection system during extreme weather events and resource limitations during concurrent megafires present ongoing operational challenges.

Recommended measures include investment landscape-scale fuel management and regional fire management agreements. Climate-adapted staffing models and infrastructure hardening are essential for effective adaptation. Future research should focus on drone swarm technologies, improved fire spread prediction models, and understanding the long-term ecosystem impacts of changing fire regimes.

The analysis demonstrates that the outcomes of wildfire management will vary substantially in climate scenarios, with sustainable development pathways offering the most effective framework for ecosystem and community protection.

5.11. Comparative analysis of data-driven and ecology-driven approaches in wildfire management

The disparities between data-driven and ecology-driven wildfire management strategies were examined in three regions: Béjaïa and Sidi Bel Abbes in Algeria and Montesinho in Portugal. This comparative analysis accounted for confounding factors such as dataset imbalance, particularly the lower recall observed in Montesinho's monitoring systems.

(1) Data-driven wildfire management

The data-driven approach used quantitative data collection through satellite imagery, IoT sensors, and drone surveillance, supported by machine learning algorithms for predictive modeling [21]. In Algerian regions, these systems enabled rapid fire detection and resource allocation through real-time data analysis, although occasionally false positives occurred due to sensor limitations. Montesinho's implementation faced challenges from incomplete historical datasets, which reduced prediction accuracy during critical periods.

(2) Ecology-driven wildfire management

Ecology-driven strategies prioritized forest health and natural fire regimes. In Algeria, controlled burns and native vegetation restoration were employed to reduce fuel loads, while Montesinho focused on habitat conservation and biodiversity-based fire mitigation. However, the slower implementation of these methods and lack of integrated data systems hindered rapid response capabilities during fire outbreaks.

Tables 3-6 (Béjaïa) and Tables 7-10 (Sidi Bel Abbes) demonstrated that data-driven tools improved early detection but sometimes overlooked ecological factors like species vulnerability. In contrast, Tables 11-14 (Montesinho) revealed that ecology-driven approaches improved long-term resilience, but struggled with scalability due to limited data integration.

(3) Hybrid strategies

Significant operational disparities were observed between the approaches to wildfire management in Algeria and Portugal. In Algeria, technological systems achieved a reduction of 72% in response times compared to conventional methods. However, ecological impact assessments were underestimated by 23% due to insufficient incorporation of biodiversity parameters [22] within predictive algorithms.

In contrast, Portuguese ecologically centered methods maintained 18% higher biodiversity preservation but incurred 41% implementation delays. These delays stemmed from the reliance on field-based evaluations and technological integration constraints.

Hybrid frameworks demonstrated superior efficacy, combining artificial intelligence forecasting with traditional ecological knowledge to achieve an overall improvement of 33%.

This integration enhanced both the temporal efficiency and the ecological preservation, resolving the core limitations of isolated approaches. The convergence of computational prediction and indigenous practices established an optimized balance between rapid intervention and the maintenance of ecosystem integrity.

Future deployments require enhanced dataset curation to mitigate regional disparities, particularly addressing Montesinho's identified data gaps. Cross-disciplinary integration is essential for addressing complex environmental challenges.

The synergistic application of satellite-guided prescribed burns and AI-monitored biodiversity corridors exemplifies optimal resource allocation: technological tools provide scalable precision, while ecological principles ensure long-term resilience. This integration transforms methodological limitations into complementary strengths, establishing a replicable framework for global adaptation to wildfire management despite climatic variability.

6. CONCLUSION AND FUTURE PERSPECTIVES

This paper demonstrates significant advances in the protection of forest safety, particularly in the Algerian provinces of Béjaïa and Sidi Bel Abbes. Using artificial intelligence and innovative techniques such as XAI, including Local Interpretable Model-agnostic Explanations) and Shapley Additive explanations, the research successfully highlights the potential of predictive modeling in assessing forest fire severity. These methods not only identify critical risk factors such as temperature, Fine Fuel Moisture Code, relative humidity, and wind speed, but also provide actionable insights into the dynamics of wildfire occurrences.

From a Conservation Forest Engineering perspective, this work is novel in its ability to pinpoint vital factors driving wildfires and offer region-specific, practical recommendations for mitigating fire risks. These include strategies such as fuel moisture management, microclimate regulation, and integrating IoT-based early warning systems, all of which contribute to reducing and controlling the severity of forest fires

The results highlight the crucial role of combining AI-based predictive analytics with conventional forest management strategies to adopt a proactive approach to preventing wildfires. Although this study represents a notable advancement, it also paves the way for numerous future research and development opportunities. A particularly promising path involves merging satellite, UAV, and IoT data analyzed through ensemble real-time ML to improve the precision and reliability of wildfire predictions, offering a more comprehensive understanding and potentially yielding more dependable and widely applicable outcomes. This layered system connects different scales (ranging from regional MODIS to sub-meter UAV data) and facilitates adaptive management in areas susceptible to fires. Furthermore, employing advanced deep learning methods, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), could enhance the capacity to identify complex, nonlinear patterns within the data, especially in regions with intricate fire dynamics like Montesinho, Portugal.

This study lays a strong foundation for the use of AI and XAI in wildfire prediction and mitigation, offering practical solutions tailored to the unique challenges of Béjaïa, Sidi Bel Abbes, and Montesinho. By addressing the limitations and exploring the future perspectives outlined above, this research has the potential to make substantial contributions to forest safety, not only in the studied regions, but also in other fire-prone areas worldwide. The continued evolution of AI-driven approaches, coupled with interdisciplinary collaboration, promises to revolutionize wildfire management, safeguarding ecosystems, communities, and biodiversity for future generations.

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REFERENCES

[1] Ruffault, J., Curt, T., Moron, V., Trigo, R. M., Mouillot, F., Koutsias, N., Pimont, F., Martin-StPaul, N., Barbero, R., Dupuy, J.L., Russo, A., Belhadj-Khedher, C. (2020). Increased likelihood of heat-induced large wildfires in the Mediterranean Basin. Scientific Reports, 10(1): 13790.https://doi.org/10.1038/s41598-020-70069-z

[2] Pausas, J.G., Keeley, J.E. (2021). Wildfires and global change. Frontiers in Ecology and the Environment, 19(7): 387-395. https://doi.org/10.1002/fee.2359

[3] Situation Report. (2023). Algeria: Forest Wildfires - Final Report, DREF Operation n° MDRDZ008. https://reliefweb.int/report/algeria/algeria-forest-wildfires-final-report-dref-operation-ndeg-mdrdz008.

[4] Bountzouklis, C., Fox, D.M., Di Bernardino, E. (2021). Environmental factors affecting wildfire burned area in South-Eastern France, 1970–2019. Natural Hazards and Earth System Sciences Discussions, 2021: 1-24. http://doi.org/10.5194/nhess-2021-174

[5] Zaidi, A. (2023). Predicting wildfires in Algerian forests using machine learning models. Heliyon, 9(7): e18064. https://doi.org/10.1016/j.heliyon.2023.e18064

[6] Abid, F., Izeboudjen, N. (2020). Predicting forest fire in algeria using data mining techniques: Case study of the decision tree algorithm. In Advanced Intelligent Systems for Sustainable Development (AI2SD'2019) Volume 4-Advanced Intelligent Systems for Applied Computing Sciences, pp. 363-370. https://doi.org/10.1007/978-3-030-36674-2_37

[7] Wu, Z., Li, M., Wang, B., Quan, Y., Liu, J. (2021). Using artificial intelligence to estimate the probability of forest fires in Heilongjiang, northeast China. Remote Sensing, 13(9): 1813. https://doi.org/10.3390/rs13091813

[8] Zhang, G., Wang, M., Liu, K. (2019). Forest fire susceptibility modeling using a convolutional neural network for Yunnan province of China. International Journal of Disaster Risk Science, 10(3): 386-403. https://doi.org/10.1007/s13753-019-00233-1

[9] Guria, R., Mishra, M., da Silva, R.M., Mishra, M., Santos, C.A.G. (2024). Predicting forest fire probability in Similipal Biosphere Reserve (India) using Sentinel-2 MSI data and machine learning. Remote Sensing Applications: Society and Environment, 36: 101311. https://doi.org/10.1016/j.rsase.2024.101311

[10] Purnama, M.I., Jaya, I.N.S., Syaufina, L., Çoban, H.O., Raihan, M. (2024). Predicting forest fire vulnerability using machine learning approaches in The Mediterranean Region: A case study of Türkiye. In IOP Conference Series: Earth and Environmental Science, 1315(1): 012056. http://doi.org/10.1088/1755-1315/1315/1/012056

[11] Faroudja, A.B.I.D. (2023). Algerian forest fires dataset. IEEE Dataport. https://doi.org/10.21227/31na-kz23, accessed Nov. 2, 2024.

[12] Dong, H., Wu, H., Sun, P., Ding, Y. (2022). Wildfire prediction model based on spatial and temporal characteristics: A case study of a wildfire in Portugal's Montesinho natural park. Sustainability, 14(16): 10107. https://doi.org/10.3390/su141610107

[13] Hersbach, H., Bell, B., Berrisford, P., Dahlgren, P., et al. (2020). The ERA5 Global Reanalysis: Achieving a detailed record of the climate and weather for the past 70 years. European Geophysical Union General Assembly, 146(730): 1999-2049. https://doi.org/10.1002/qj.3803

[14] Carroll, C., Mahony, C.R. (2025). Sources of uncertainty in estimation of climate velocity and their implications for ecological and conservation applications. Conservation Science and Practice, e13296. https://doi.org/10.1111/csp2.13296

[15] Van Wagtendonk, J.W. (1977). Refined burning prescriptions for Yosemite National Park (No. 2). US National Park Service.

[16] Gebrechorkos, S.H., Peng, J., Dyer, E., Miralles, D.G., Vicente-Serrano, S.M., Funk, C., Beck, H.E., Asfaw, D.T., Singer, M.B., Dadson, S.J. (2023). Global high-resolution drought indices for 1981–2022. Earth System Science Data Discussions, 15(12): 5449-5466. https://doi.org/10.5194/essd-15-5449-2023

[17] Rodrigues, M., Jiménez-Ruano, A., Gelabert, P.J., de Dios, V.R., Torres, L., Ribalaygua, J., Vega-García, C. (2023). Modelling the daily probability of lightning-caused ignition in the Iberian Peninsula. International Journal of Wildland Fire, 32(3): 351-362. https://doi.org/10.1071/WF22123

[18] Tramblay, Y., Koutroulis, A., Samaniego, L., Vicente-

Serrano, S. M., Volaire, F., Boone, A., Page, M.L., Llasat, M.C., Albergel, C., Burak, S., Cailleret, M., Kali, K.C., Davi, H., Dupuy, J.L., Greve, P., Grillakis, M., Hanich, L., Jarlan, L., Martin-StPaul, N., Martínez-Vilalta, J., Polcher, J. (2020). Challenges for drought assessment in the Mediterranean region under future climate scenarios. Earth-Science Reviews, 210: 103348. https://doi.org/10.1016/j.earscirev.2020.103348

[19] Lebiar, I.E. (2023). Modeling wildfire risk in the aurès region: Spatial and statistical analysis for assessment and conservation. University of Batna, Algieria, Master Thesis. https://doi.org/10.13140/RG.2.2.32799.74401/1

[20] Gemma, R. (2023). Climate change analysis: A comprehensive study about portugal's shifts in temperatures and precipitation within sights on their causes and mitigation strategies. Master's thesis, Universidade NOVA de Lisboa (Portugal).

[21] Ramil Brick, E.S., Holland, J., Anagnostou, D.E., Brown, K., Desmulliez, M.P. (2022). A review of agroforestry, precision agriculture, and precision livestock farming—The case for a data-driven agroforestry strategy. Frontiers in Sensors, 3: 998928. https://doi.org/10.3389/fsens.2022.998928

[22] Lau, J.D. (2020). Three lessons for gender equity in biodiversity conservation. Conservation Biology, 34(6): 1589-1591. https://doi.org/10.1111/cobi.13487