

Evaluation of risk scenarios in Ecuador using Visible Infrared Imaging Radiometer Suite remote sensing, ERA5-Land climate data, and XGBoost

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ABSTRACT

The present study aims to develop and optimize a spatial risk scenarios model for forest fires in Ecuador through the integration of machine learning and satellite remote sensing. To this end, 103,224 historical records of thermal anomalies captured by the VIIRS sensor were processed, along with five continuous meteorological variables from the ERA5-Land global reanalysis, spatial coordinates (latitude and longitude), and temporal indicators (month of the year), spanning the period between 2015 and 2025. The methodology was based on the construction of a 5-kilometer resolution spatial grid coupled with the XGBoost classification algorithm, designed to efficiently manage class imbalance in the face of extreme climate events. The computational system achieved an accuracy level of 81% on the test set, validating its robustness with a true positive rate of 0.86 and an area under the ROC curve of 0.8382. Furthermore, the feature importance analysis determined that precipitation deficits and seasonal timing act as the primary drivers of ignition risk, exerting a significantly greater influence than surface temperature, concluding that this scalable and open-access tool allows for high-precision mapping of vulnerable areas in the Andean and coastal regions through scenario-based experiments, aiming to optimize the distribution of state preventive resources against the constant threat of global warming.

Keywords: forest fires, machine learning, XGBoost, climate risk, spatial risk scenarios, remote sensing.

INTRODUCTION

Wildfires represent one of the most critical environmental threats globally, driving severe ecosystem degradation, biodiversity loss, and significant emissions of greenhouse gases that further exacerbate global climate change (Pausas & Keeley, 2021; Illarionova et al., 2025; Li et al., 2026). Over recent decades, the rapid rise in global temperatures, the lengthening of seasonal droughts and changes in rainfall patterns have led to extreme weather conditions, causing a critical increase in water stress on biomass and in the availability of dry fuel (Abatzoglou et al.,

2019; Zubieta et al., 2021; Gutierrez et al., 2025). Against this backdrop, the ability to predict the occurrence and spread of fires have become essential for risk management, the efficient allocation of resources and the planning of mitigation strategies at regional and national levels (Agrawal et al., 2023; Nasourinia & Passi, 2025; Boris, 2025).

Despite the urgent necessity for reliable early-warning systems, conventional fire prediction models have significant operational limitations. Physical simulation tools and spatial propagation tools, such as FARSITE, are often computationally intensive and require the comprehensive integration of field variables that are difficult to

access on a large scale (Agrawal *et al.*, 2023; Liu *et al.*, 2025). Furthermore, many of the recent predictive or risk scenarios models based on machine learning are restricted to very specific local or regional areas of application, which makes it difficult to generalise them to other geographical areas with complex topoclimatic dynamics (Agrawal *et al.*, 2023; Lorent *et al.*, 2025). This reliance on heavy architectures or spatially fragmented data highlights the need to develop scalable approaches based on freely accessible data with high temporal and spatial resolution.

In response to these challenges, combining satellite remote sensing with atmospheric reanalysis has established itself as a robust and standardised alternative. The use of observations of thermal anomalies and hotspots provided by the VIIRS (Visible Infrared Imaging Radiometer Suite) sensor, with a spatial resolution of 375 metres, enables the accurate detection of incipient fires and small-scale fires that typically escape detection by lower-resolution sensors (Son *et al.*, 2024; Eaturu & Vadrevu, 2025).

By combining these space-based observations with meteorological and surface variables from the Copernicus ERA5-Land reanalysis – such as surface temperature, soil volumetric moisture and wind speed – it is possible to uniformly characterise the environmental drivers of fire (Kudláčková *et al.*, 2025; Durlević *et al.*, 2026). Accordingly, to process these large spatial tabular matrices, machine learning algorithms and in particular ensemble methods based on decision trees (Yel *et al.*, 2026), such as XGBoost have demonstrated remarkable analytical superiority in capturing non-linear relationships and handling imbalanced data sets with high efficiency, outperforming traditional statistical classifiers (Mohajane *et al.*, 2021; Agrawal *et al.*, 2023; Tavakoli *et al.*, 2024).

Based on this background, the aim of this study is to develop and optimize a spatial risk scenarios model for forest fires in Ecuador by integrating VIIRS satellite hotspots and ERA5-Land, and spatio-temporal components were processed using the XGBoost algorithm (Hidalgo *et al.*, 2025). Unlike conventional methodologies, this approach capitalises on the availability of global open data to overcome computational scale limitations, offering a scalable, high-precision solution adapted to the complex topography of Ecuador's Andean and coastal regions. (Arias *et al.*, 2024; Facuy *et al.*, 2026). According to Carrion *et al.*, (2023) the system should be implemented

through an interactive web interface. Therefore, this study incorporates this recommendation by implementing an interactive web interface for projecting climate risk scenarios under future climate variations (Balaguer *et al.*, 2026).

MATERIALS AND METHODS

Materials

Historical records of active thermal anomalies and fire hotspots across the coastal and Andean regions of Ecuador (2015–2025) were acquired from NASA's Fire Information for Resource Management System (FIRMS) (Durlević *et al.*, 2025; Yel *et al.*, 2026). These spatial records were acquired using the Visible Infrared Imaging Radiometer Suite (VIIRS) satellite sensor, which provides observations at a nominal spatial resolution of 375 metres, surpassing the ability of traditional sensors to identify fire hotspots under the dense cloud cover typical of this region (Son *et al.*, 2024). According to Schreck *et al.*, (2023), the key elements must be extracted from this database, which included the geographical coordinates of origin (latitude and longitude) and the date on which the thermal event was recorded.

To structure the dataset over the 11-year observation window, the study area was discretized into a $0.1^\circ \times 0.1^\circ$ regular geographic grid, corresponding to spatial grid cells of approximately 5×5 km (Li *et al.*, 2026; Durlević *et al.*, 2026). Through this processing, a tabular dataset was compiled in which each cell was assigned a binary classification, where a value of 1 indicated the detection of an active fire hotspots in a specific month and year, whilst a value of 0 indicated the absence of fire in that cell. The timestamp of each event was processed to extract the month of the year, incorporating seasonality (month) into the matrix structure. The spatial distribution of the processed satellite detections across Ecuadorian territory is illustrated in Figure 1.

In addition, historical records from the ERA5-Land atmospheric reanalysis, provided by the Copernicus Climate Data Store, were downloaded, covering the same time frame from 2015 to 2025. This dataset provides a consistent picture of the evolution of land-based variables at an improved spatial resolution of 9 kilometres, which is essential for assessing water risk in complex mountainous terrain. Five climatological variables were

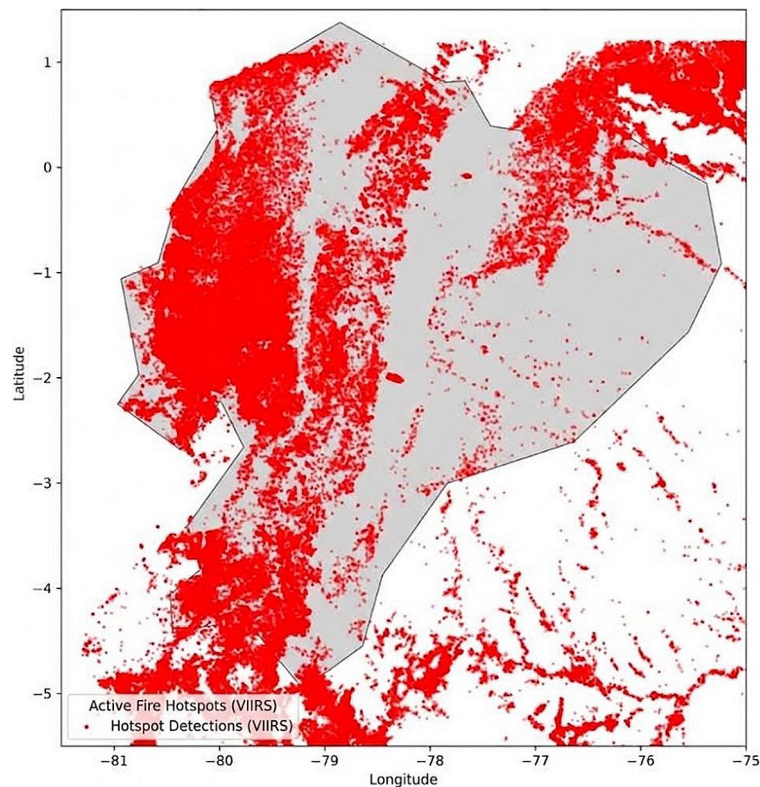


Figure 1. Spatial distribution of hotspots detected by VIIRS (2015–2025)

extracted from this model in the form of monthly averages and applied to each cell of the spatial grid:

- Skin temperature - skt.
- Volumetric soil water layer 1 – swvl1.
- Total precipitation - tp.
- 10 m u-component of wind - u10.
- 10 m v-component of wind - v10.
- Grid_lat
- Grid_lon
- Month.

Orthogonal wind components were processed in order to enabled the calculation of their actual magnitude, whilst the temperature was converted from degrees Kelvin to Celsius. Finally, the integration of VIIRS sensor data with ERA5-Land atmospheric parameters and the spatio-temporal

attributes resulted in a consolidated data matrix for input into the machine learning engine using the Python programming language, version 3.11.9. Table 1 summarizes the analytical variables used in the research.

Methods

For the purposes of this project, each spatial cell generated from the 0.1-degree grid covering Ecuadorian territory was processed individually to integrate the historical records; consequently, the binary ignition status derived from the VIIRS hotspot database, together with the five continuous atmospheric variables extracted from the ERA5-Land reanalysis, were fed into the XGBoost machine learning model as a training dataset.

Table 1. Variables used in the risk scenario model and their sources

Variable	Source
Incident coordinates (Latitude/Longitude)	Suomi NPP satellite (VIIRS 375-metre sensor)
Seasonal variation month	Suomi NPP satellite (VIIRS 375-metre sensor)
Earth's surface temperature	ERA5-Land reanalysis
Total monthly precipitation	ERA5-Land reanalysis
Soil volumetric moisture content (0–7 cm)	ERA5-Land reanalysis
Wind speed magnitude (U/V)	ERA5-Land reanalysis

In this way, the system analyzed the algorithm's accuracy for classifying fire-risk areas and determined the relative importance of each climatic factor in the decision-making process, establishing a structured workflow whose logical phases of processing, modelling and evaluation are outlined in Figure 2.

It is important to mention, the entire computational workflow was developed in Python 3.11.9, utilising the Pandas, scikit-learn and XGBoost libraries. The spatial data and complete source code, ranging from the preprocessing on the NetCDF files to the block-based spatial evaluation and the serialized model in .joblib format, are freely available to ensure the study's full reproducibility.

Processing

VIIRS sensor's hotspot records and the ERA5-Land meteorological observations cover complete time series from 2015 to 2025, the research structured the analysis by evaluating only the fire occurrences documented up to the end of the recorded historical cycle, thereby ensuring chronological correspondence between the two data sources, furthermore, beyond the precise location of the fire's origin, it is essential to consider the climatic variability of the surrounding area in order to understand the dynamics of ignition, given that atmospheric factors such as surface temperature, low rainfall and the drying effect of the wind act as direct drivers of the

desiccation of plant biomass (Agrawal *et al.*, 2023; Illarionova *et al.*, 2025).

For this reason, for each hotspot detected by the satellite, the atmospheric data corresponding to the month in which it occurred were processed directly from the NetCDF-format downloads from Copernicus, consolidating monthly averages to capture the structural climatic conditions that favour the outbreak of fire, in contrast to instantaneous meteorological variations which are less useful for medium-term projections. Similarly, to address the challenge of spatial autocorrelation, where adjacent areas exhibit redundant environmental characteristics (Schag *et al.*, 2022; Agrawal *et al.*, 2023). The spatial and atmospheric data were interpolated and averaged within the 5 by 5 kilometers geographical grid mentioned previously, as shown in Figure 3.

Finally, the binary 'true' or 'false' classification for each quadrant, together with the eight continuous atmospheric variables were consolidated and organised into a Python DataFrame using the pandas library, serving as the final matrix for the computational training phase.

Modelling

It is important to mention that recent studies on wildfires using machine learning have demonstrated the superiority of ensemble methods over traditional statistical approaches (Tavakoli *et al.*, 2024; Agrawal *et al.*, 2023; Yel *et al.*, 2026), the modelling process was carried out exclusively

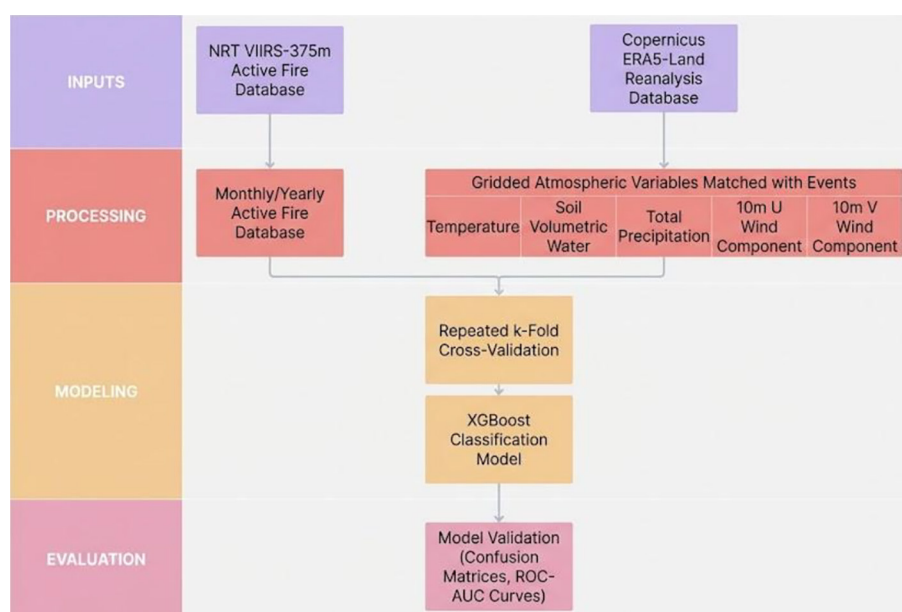


Figure 2. A flowchart illustrating the logical subsystems in the methodology of this research

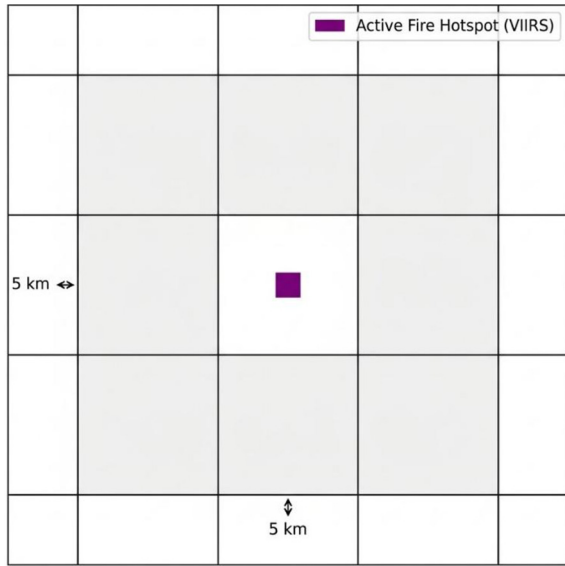


Figure 3. An example of the 5 km by 5 km geographical grid used for the resampling of ERA5-Land climate variables

using the Extreme Gradient Boosting (XGBoost) classification algorithm, due to its proven efficiency in handling complex tabular matrices and its intrinsic ability to compensate for class imbalance. To carry out this computational implementation, the scikit-learn and XGBoost libraries of the Python programming language were used (Tavakoli *et al.*, 2024).

To ensure a rigorous model assessment and eliminate the spatial autocorrelation (data leakage) inherent in simple random partitions, the dataset was structured using a spatial block cross-validation scheme.

To this end, the base grid was internally grouped into geographical macro-blocks measuring 0.5 by 0.5 degrees. Using the GroupShuffleSplit function from the scikit-learn library, the data were split, with 80 per cent of the macro-blocks allocated to the training process and 20 per cent of the geographically independent blocks retained exclusively for validation; the main training set was used to internally fine-tune the classifier, enabling the algorithm to assimilate the complex non-linear relationships between weather conditions, spatial location and seasonality in relation to the presence of fire. The 20 per cent test set was kept completely hidden from the model throughout the training phase and was used exclusively to assess the system's generalization ability and determine its overall accuracy in the face of entirely new weather scenarios.

Evaluation

For this study, two evaluation metrics commonly used in binary classification were employed: accuracy, which denotes the percentage of correctly classified observations, and the area under the curve (AUC), derived from the receiver operating characteristic (ROC) curve. Consequently, the accuracy for the XGBoost model was determined using the confusion matrix, based on the values for true positives (TP), false positives (FP), true negatives (TN) and false negatives (FN), calculated as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \times 100\% \quad (1)$$

Additional metrics were incorporated, whereby the true positive rate (TPR) refers to the percentage of positive observations correctly classified using the following formula:

$$\text{TPR} = \frac{TP}{TP + FN} \quad (2)$$

Whilst the true negative rate (TNR) denotes the percentage of negative observations correctly classified according to the equation:

$$\text{TNR} = \frac{TN}{TN + FP} \quad (3)$$

One validation test was carried out, comparing the model's TPR with its false positive rate (FPR) by analysing the ROC curve, where the FPR represents the proportion of incidents that the model incorrectly predicted as fires out of the total number of non-fire incidents, expressed as:

$$\text{FPR} = \frac{FP}{TN + FP} \quad (4)$$

The area under the curve (AUC) serves as a widely accepted measure for validating performance; AUC scores of 0.5 indicate random classification, values between 0.5 and 0.7 are considered poor, ranges between 0.7 and 0.9 represent moderate performance, and scores above 0.9 are classified as excellent. Finally, the importance of the variables is fundamental to understanding which climatic factors carry the greatest weight in fire classification; therefore, a feature importance analysis specific to the algorithm was incorporated to quantify the relative contribution of each variable (climatological, spatial and temporal) to reducing the decision tree's error, thereby enabling the identification of the system's sensitivity to variations in temperature seasonality and precipitation during the projection of risk scenarios.

RESULTS

The results obtained from the computational modelling process were evaluated in terms of accuracy analysis, validation of performance metrics and the identification of the feature importance based on the five ERA5-Land atmospheric variables used in this study, in accordance with the previously established methodology.

Model accuracy analysis

For the XGBoost classification model implemented, the accuracy score was determined by evaluating the number of correctly classified instances out of the total number of risk predictions within the 20 per cent test set generated using cross-validation by spatial blocks; consequently, the system achieved an overall accuracy of 81 per cent when processing 113526 hidden geospatial observations, demonstrating the algorithm's high capacity to discern spatial patterns of ignition under the complex climatic variations of the analyzed territory. Table 2 presents the quantitative performance of the optimized classifier (Nasourinia & Passi, 2025; Nawazuzzoha *et al.*, 2026; Ouazri *et al.*, 2026).

Confusion matrix

The validation of the algorithm's performance was structured using a confusion matrix, in which true positives (TP) are represented in the bottom-right quadrant, true negatives (TN) in the top-left quadrant, false positives (FP) in the top-right quadrant and false negatives (FN) in the

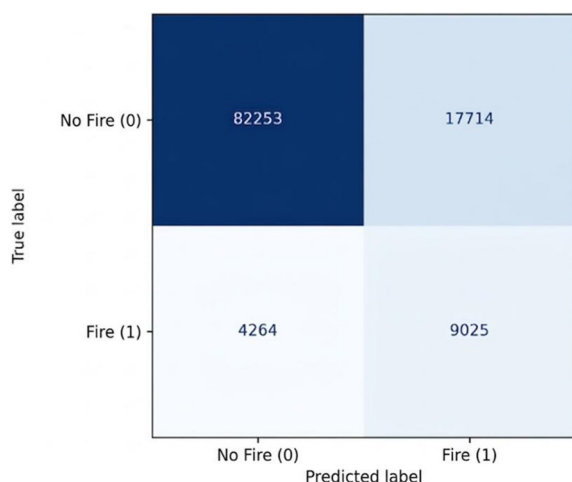


Figure 4. Confusion matrix

Table 2. Accuracy score of the machine learning model used

Model type	Accuracy score
XGBoost classification	83%

bottom-left quadrant; consequently, the implemented XGBoost model demonstrated highly effective performance for spatial risk analysis, recording a true positive rate (TPR) of 0.86 and a true negative rate (TNR) of 0.82, confirming that the balanced weight parameter allocation worked optimally to prioritize the detection of the minority fire class (Tavakoli *et al.*, 2024; Elia *et al.*, 2020; Moumane *et al.*, 2025) (Figure 4).

AUC score

In addition, the overall risk evaluation performance was quantified by calculating the area under the curve (AUC) based on the receiver operating characteristic (ROC) curve, yielding a value of 0.8382 for the XGBoost model (Dupuy *et al.*, 2020), which indicates the system's excellent ability to statistically differentiate between geographical cells with a high risk of ignition and safe cells under variable weather conditions (Lorent *et al.*, 2025; Yel *et al.*, 2026) (Figure 5).

Identification of key variables

Finally, the relative importance of each of the climatic characteristics used during the algorithm's training was identified, determining through the minimization of the internal loss

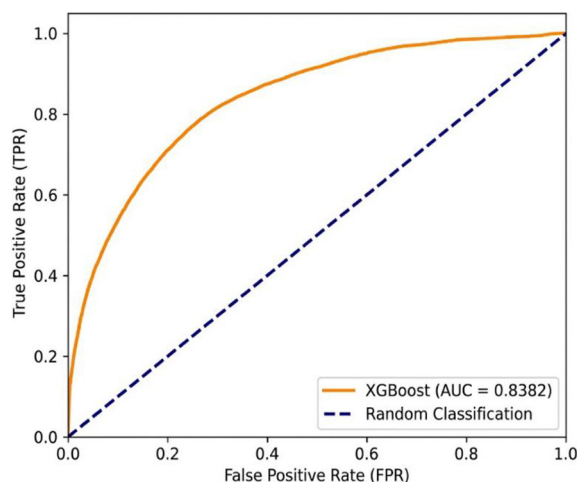


Figure 5. Curve ROC

function which meteorological factors carry the greatest risk evaluation weight for spatial decision making (Zaidi, 2023), the graphical results clearly illustrate that precipitation (with a relative importance of ~26 per cent), seasonality or month of occurrence (~19 per cent), and soil moisture (~16 per cent) act as the key environmental and temporal drivers in establishing critical fire probability thresholds. Contrary to preliminary assumptions, temperature was found to have a secondary impact on the model (~9%), ensuring that the interactive simulations respond with high fidelity to direct changes in the rainfall regime and the time of year within the projected environmental scenario (Zubieta *et al.*, 2021; Hidalgo *et al.*, 2025; Arias *et al.*, 2024) (Figure 6).

DISCUSSION

This project analyzed 103,224 spatial cell occurrences covering the territory of Ecuador during the period from 2015 to 2025, integrating open-access data from NASA's VIIRS remote sensing sensor and the ERA5 -Land climate re-analysis, thereby developing and optimizing a machine learning model based on the XGBoost algorithm to evaluate risk of forest fire ignition by assimilating five continuous atmospheric variables and 3 explicit spatio-temporal determinants coupled to the local topography.

It is essential to recognize and address a methodological limitation present in much of the previous literature: the use of simple random splits in spatio-temporal data. Splitting matrices of this

nature at random results in contiguous cells or consecutive days being included in both the training and test sets, which leads to autocorrelation and data leakage, thereby artificially inflating the models' performance metrics (Durlević *et al.*, 2026; Suheb *et al.*, 2026).

To mitigate this bias, this study implemented rigorous validation using independent spatial blocks. Thanks to this isolated validation architecture, the XGBoost classification model demonstrated high performance, achieving a realistic accuracy score of 81 per cent and an AUC of 0.8382. This performance metric demonstrates the algorithm's true spatial generalisation capability when faced with geographically hidden ecosystems and meteorological data, cementing XGBoost's position as one of the most robust risk evaluation approaches in recent literature on wildfires (Hidalgo *et al.*, 2025). Furthermore, the integration of thermal anomaly data from satellite sensors such as VIIRS ensures a much higher spatial resolution, achieving a level of accuracy that surpasses the detection capabilities of older satellite platforms (Agrawal *et al.*, 2023; Lorent *et al.*, 2025).

A crucial finding arising from the empirical extraction of feature importance is the hierarchy of environmental drivers. The data categorically demonstrated that precipitation deficits, seasonal timing (month of the year) and volumetric soil moisture loss are the true primary drivers of fire in the model (Li *et al.*, 2025). This refutes the preliminary notion that surface temperature is the dominant factor, bringing this study into line with recent findings in Andean and subtropical environments

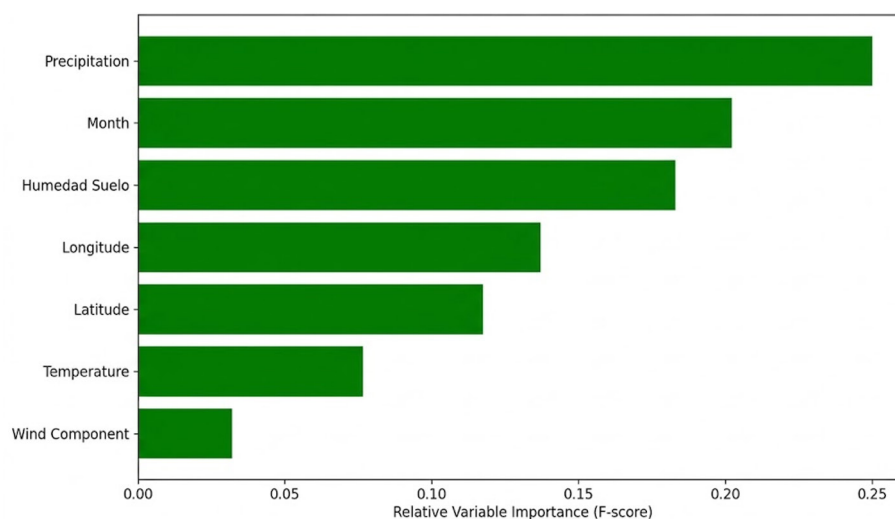


Figure 6. Feature importance generated by the XGBoost model

where water stress in biomass dictates vulnerability to ignition (Illarionova *et al.*, 2025)

This integration of highly refined global climate databases enables a much more holistic and cost-effective approach to fire modelling at a national scale, overcoming the shortcomings of traditional two-dimensional physical fire spread models (such as FARSITE), which are often computationally intensive and require constant manual measurement of fuel loads in the field (Gutierrez *et al.*, 2025). Consequently, the intrinsic geographical flexibility of the VIIRS and ERA5-Land satellite observations ensures that this XGBoost classifier can be rapidly adapted to other Andean or coastal regions, overcoming the technological limitations of previous local tools (Zubieta *et al.*, 2021).

Therefore, equitable allocation of state resources is essential to protect the most vulnerable populations from crises arising from climate change (Illarionova *et al.*, 2025). In Ecuador, rural areas located throughout the inter-Andean region and agricultural areas on the coast often lack the rapid-response infrastructure needed to combat large-scale fires. This shortfall not only exacerbates crop loss and the degradation of productive

soil, but also compromises the hydrological function and the provision of ecosystem services by the Andean páramos, directly affecting the food and economic security of rural communities. With limited institutional budgets for environmental mitigation, it is imperative to optimize the distribution of emergency equipment, forest fire brigades and conservation funds in a judicious and targeted manner.

Therefore, the interactive web interface generated by this XGBoost model must be interpreted strictly as a platform for conducting experiments based on simulated scenarios, and not as a validated model for forecasting future climate conditions (Pausas & Keeley, 2021). This tool enables the projection of sensitivity scenarios in response to water and heat stress (for example, anomalous temperature increases and percentage reductions in precipitation), giving the authorities the ability to deploy preventative resources in the most vulnerable sectors before fires break out a pressing need in Andean regions prone to prolonged seasonal droughts, a pressing need in Andean regions prone to prolonged seasonal droughts (Hidalgo *et al.*, 2025; Facuy *et al.*, 2026) (Figure 7).

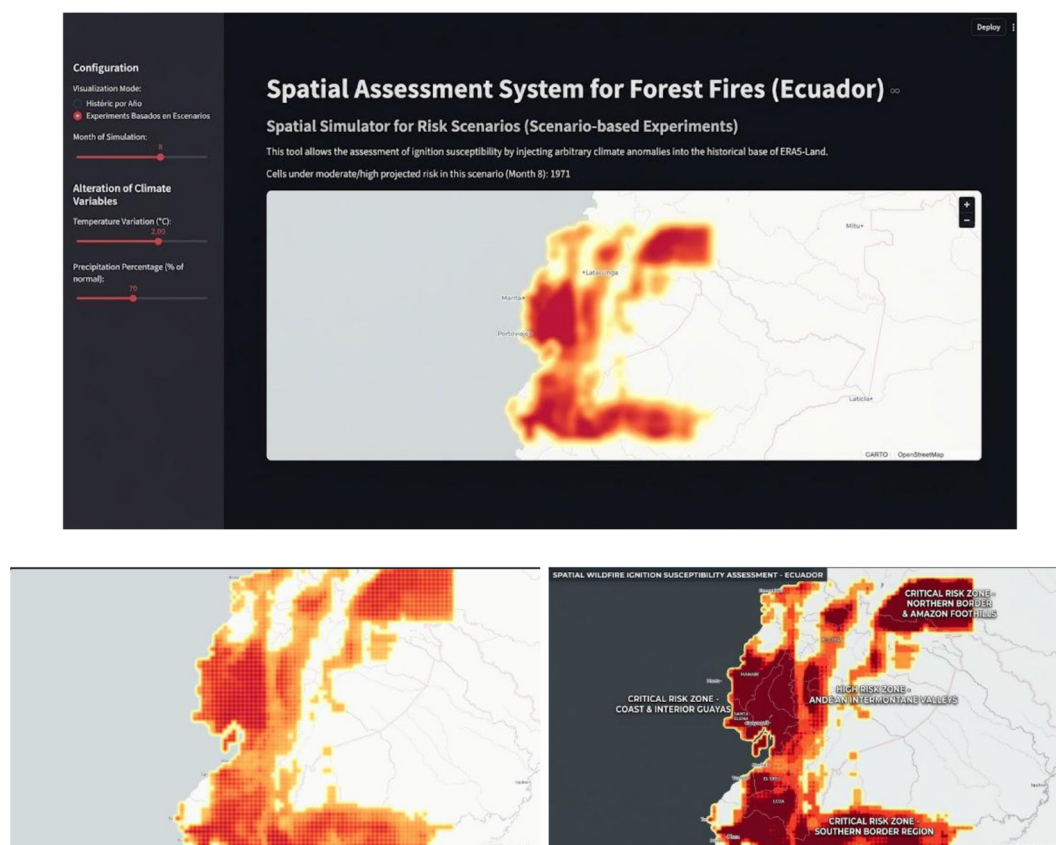


Figure 7. Spatial map of Ecuador showing vulnerable geographical areas at high risk of fire

Furthermore, this study succeeded in quantifying the importance of atmospheric characteristics within the architecture of the machine learning model; however, it is important to recognise that the climatic variables assessed in this research are neither exhaustive nor absolute (Carrión *et al.*, 2023). For example, this study does not incorporate the direct impact of human behaviour on changes to the distribution of plant fuel, nor does it address long-established cultural practices such as controlled agricultural burning, which represent a primary cause of accidental fires in Ecuador that cannot be explained by strictly meteorological factors.

Consequently, future research should incorporate socio-demographic indicators and land-use data to better understand how human activity interacts with climate change in fire evaluation risk (Agrawal *et al.*, 2023; Kondylatos *et al.*, 2022). Although the XGBoost model developed demonstrates robust technical accuracy based on spatial block validation of historical climate records, natural ecosystems possess complex ecological dynamics that tabular matrices do not always fully capture (Hidalgo *et al.*, 2025), requiring future prediction architectures to be dynamic and adaptive in order to respond accurately to constantly evolving environmental and human conditions (Facuy *et al.*, 2026; Gutierrez *et al.*, 2025).

CONCLUSIONS

This research demonstrated the technical and operational feasibility of integrating VIIRS sensor space-based heat signature observations with meteorological variables from the ERA5-Land reanalysis and spatiotemporal components for the evaluation risk of forest fires in Ecuador, succeeding in developing a machine learning model based on the XGBoost algorithm that overcame the processing limitations of traditional methodologies by implementing a rigorous spatial block-based cross-validation scheme to eliminate data leakage; the model achieved a realistic accuracy of 81 per cent alongside an AUC of 0.8382. Furthermore, the analysis quantified that precipitation deficits and seasonality (month) act as the primary drivers of risk, outweighing the influence of temperature. Consequently, this performance metric ensures high analytical reliability for effectively distinguishing between safe areas and 5-kilometre geographical quadrants with an imminent risk of ignition.

The implementation of this computational classifier via an interactive interface demonstrated that the analysis of climatic anomalies through experiments based on simulated scenarios enables the precise mapping of vulnerable areas in the Andean and coastal regions, providing the relevant authorities with a scalable, open-access tool to optimise the allocation of preventive resources within limited budgets; however, to improve the accuracy of these experimental tools, future research must incorporate variables relating to land use, population growth and anthropogenic agricultural practices, ensuring a fully comprehensive approach that assesses the complex ecological interaction between global warming and human behavior on ecosystems.

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