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Wildfire Risk Assessment through Machine Learning-Based Metamodels

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Abstract. One of the main threats to tropical ecosystems is the occurrence of wildfires, which simultaneously endanger animal communities and human health due to the destructive nature of the phenomenon. To address this, a variety of disaster prediction algorithms have been developed; however, these still present gaps that limit their precision and applicability. In response, this study proposes to take advantage of the physical and biological complexity of the "Cumbres de Monterrey" National Park, located in Nuevo León, Mexico, for the categorization of its territory based on a fire risk assessment using ensemble metamodels that integrate seven Machine Learning algorithms. These models are trained with wildfire records from the fire seasons between 2013 and 2022, along with the spatiotemporal variation of physical, biological, and demographic components. The predictive potential of both models and metamodels is evaluated using six different metrics. The comparison reveals that the metamodels exhibit fluctuating effectiveness in classifying risk zones in the region, ranging from 73.77% in 2020 to 91.3% in 2019. The results provide a robust methodological framework for wildfire prediction, overcoming the limitations of traditional Machine Learning approaches through the implementation of ensemble-based metamodels.

Keywords: Artificial Intelligence, forest fires, conservation, remote sensing, wildfire prediction.

1 Introduction

Fire has remained a key factor in the development of human societies and in the evolution of ecosystems worldwide, due to its influence on ecological processes such as species regeneration, nutrient cycling, and landscape configuration (Bowman *et al.*, 2009; Moritz *et al.*, 2014).

However, when this natural and stochastic phenomenon escapes human control, it is referred to as a wildfire. In particular, those affecting areas with natural vegetation cover are classified as forest fires, which generate significant disturbances in both ecological and anthropogenic systems. One such victim of these incidents is the Cumbres de Monterrey National Park (CMNP), located in the state of Nuevo León, México, has been affected by these incidents (Fueyo-MacDonald, 2013; CONANP, 2020). In most cases, the origins of these disasters are anthropogenic, such as waste pollution from the Monterrey Metropolitan Area (Fueyo-MacDonald, 2013), soil stress, and the repurposing of areas for tourism activities (Narváez-Torres & Lazcano-Villareal, 2013).

Furthermore, due to its highly rugged geomorphology, this region exhibits a high degree of climatic dynamism (Alanís-Flores & Velazco-Macías, 2013), which causes variability in average temperatures and annual precipitation levels that influences the persistence of wildfire events (Jiménez-Pérez *et al*., 2013).

The highly dynamic and destructive nature of forest fires makes it imperative to implement preventive measures to avoid their uncontrolled spread (McKenzie *et al*., 2004; Moritz *et al*., 2014). Currently, there are regional action protocols in place for the immediate management of these events, such as the Fire Management Program (SCMF, 2017). However, their effectiveness critically depends on the availability of reliable predictive models that allow for the optimal distribution of primary response resources (Stocks & Martell, 2016; McGovern *et al*., 2017; Tymstra *et al*., 2020).

Over the last two decades, with advances in data analysis and artificial intelligence, multiple methodologies have been proposed to achieve reliable predictions of wildfires in natural areas. These range from simple models that incorporate and synthesize expert perspectives such as Multi-criteria Decision Making (MCDM) (Eskarandi *et al*., 2015); basic statistical archetypes like Logistic or Multinomial Regression (Thai Pham *et al*., 2020); to more complex algorithms that include Machine Learning methods such as Neural Networks (Barmpoutis et al., 2020), Support Vector Machines (SVM) (Özbayoglu & Bozer, 2012), Fuzzy Logic (Neuro-fuzzy) (Thai Pham *et al*., 2020), Bayesian Networks (Thai Pham *et al*., 2020), and Random Forests (Arkin *et al*., 2019), among others (Abid, 2021; Preeti *et al*., 2021).

The main challenge in establishing these models lies in the strong dependency of wildfires on climatic variables (McKenzie et al., 2004; Moritz *et al*., 2014), which introduces a substantial uncertainty component in occurrence modeling. For this reason, these models frequently analyze the physical factors of the terrain (climatology, topography, and hydrology) (Jain *et al*., 2020; Malik *et al*., 2021; Xie et al., 2022). However, only a few models consider biological factors (fuel type and load, vegetation composition, land use) (Cencerrado *et al*., 2014; Lauer *et al*., 2017), while demographic factors are often actively overlooked (Kondylatos *et al*., 2022).

These omissions create significant predictive gaps, as they are unable to objectively analyze the multidimensional complexity of forest fires (Cheng & Wang, 2008; Kozik *et al*., 2013; Jain *et al*., 2020). As a result, it becomes necessary to synergistically integrate a considerable number of base models whose predictive strengths mutually compensate for their individual limitations. This can be achieved through the development of ensemble metamodels, which combine heterogeneous architectures (physical, statistical, and machine learning models) for the development and selection of multiple submodels through systematic variation of hyperparameters (tuning) and consensus algorithms. These models also implement adaptive weighting mechanisms that optimize the relative contribution of each submodel, generating consolidated estimates with lower bias and variance than individual models (Nguyen *et al*., 2021).

Currently, there are few initiatives in the region exploring the application of autonomous machine learning algorithms for forest fire prediction. This scarcity has led to uncertainty regarding their operational viability and actual effectiveness among the stakeholders responsible for the conservation of the CMNP.

Given this context, the present study proposes to develop an integrative metamodel that generates predictive consensus from multiple autonomous algorithms, quantitatively evaluates the classification capacity of vulnerable areas using spatially explicit metrics, estimates risks based on hazard and exposure indicators, and contributes to the technical debate on the applicability of these methodologies in protected natural systems.

2 Methodology

2.1 Study Area

The Cumbres de Monterrey region, designated as a Protected Natural Area (ANP, for its initials in Spanish) with National Park status on November 24, 1939 (DOF, 1939), currently encompasses an area of 1,779.95 km² and is located across the states of Nuevo León and Coahuila de Zaragoza (Fig. 1). This designation was later redefined by an ordinance issued on November 17, 2000 (DOF, 2000).

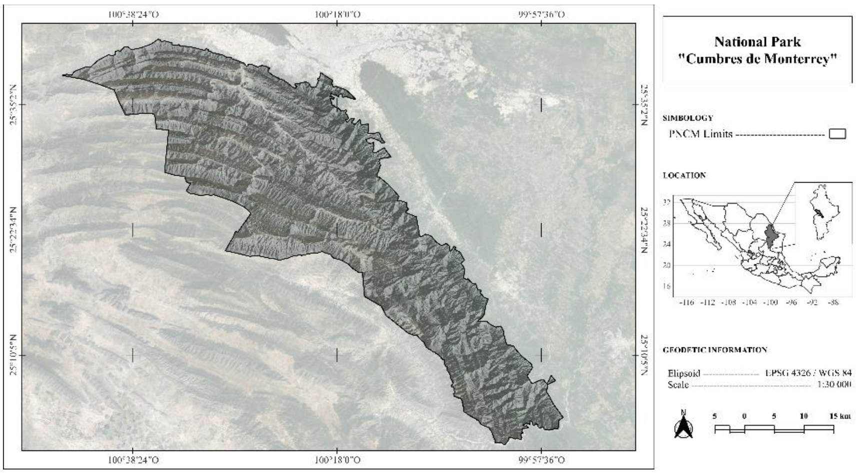

Fig. 1. Geographic location of the ANP "Cumbres de Monterrey" National Park.

2.2 Fire Records

Through a query conducted on the databases of the Fire Danger Prediction System (SPPIF, for its initials in Spanish) (CONAFOR, 2024) and the Fire Information for Resource Management System (FIRMS) (NASA, 2024), historical records of wildfires occurring within the CMNP during the fire season -February to May- from 2013 to 2022 were collected.

A similar amount of pseudo-absence points *(background points*) was artificially added to the true wildfire records for each year, ensuring spatial randomness under the condition that their origin would not fall outside the delimited region nor overlap geographically with the actual records.

2.3 Predictors

Climatic. To measure regional temperature and humidity factors, annual aerial imagery from the Landsat 8 OLI/TIRS satellite was used, restricting the selection to photographs produced between February and May, considering only those with minimal cloud cover.

The analysis of the Land Surface Temperature (LST) is applied (Eq. 1):

$$LST = \frac{T_B}{1+(\lambda \cdot \frac{T_B}{\rho \cdot \ln \epsilon})} \tag{1}$$

$\mathbf{T_B}$	=	Brightness temperature or radiance
$\boldsymbol{\lambda}$	=	Wavelength of emitted radiance (11.5 µm)
$\boldsymbol{\rho}$	=	$h \times c/\sigma = 1.438 \times 10^{-2}$ mK[1]
$\boldsymbol{\varepsilon}$	=	Surface emissivity

Similarly, for the estimation of humidity in the National Park, the analysis of the Normalized Difference Moisture Index (NDMI) is used (Eq. 2):

$$NDMI = \frac{(NIR-SWIR)}{(NIR+SWIR)} \xrightarrow{In\ Landsat\ 8} \frac{(Band\ 5-Band\ 6)}{(Band\ 5+Band\ 6)} \tag{2}$$

Topographic. The variance in elevation of the topography is measured using the N25W100 and N25W101 digital elevation models extracted by the Shuttle Radar Topography Mission (SRTM) (NASA, 2000), through which the analysis of slope inclinations and aspect is performed, considering solar incidence.

Hydrological. Each of the surface watercourses within the CMNP is examined and georeferenced to estimate the Euclidean distance (proximity) from each point in the region to these watercourses.

Ecosystem-based. Using satellite imagery from the Landsat 8 OLI/TIRS satellite, annual Normalized Difference Vegetation Indices (NDVI) relevant to the same time periods established in this study are obtained (Eq. 3):

$$NDVI = \frac{(Red-NIR)}{(Red+NIR)} \xrightarrow{In\ Landsat\ 8} \frac{(Band\ 5-Band\ 4)}{(Band\ 5+Band\ 4)} \tag{3}$$

σ = Boltzmann constant, h = Planck constant, c = Speed of light.

Additionally, the Land Use and Vegetation Classification Series VII (INEGI, 2021) was employed to categorize the main ecosystems and urban areas within the CMNP territory.

Demographic. The proximity of each territorial point to the localities listed in the 2020 Population and Housing Census (INEGI, 2021) and to tourist routes recorded in the AllTrails platform up to 2022 was analyzed.

2.4 Base Models

To construct the metamodel, the following base ensemble models were defined and trained in parallel using the R v.4.4.3 "Trophy Case" environment (Table 1):

Table 2. Structure for defining the base ensemble models.

Model	Permutation Levels	Library	Function	Arguments	Total Submodels
RL	3	glmnet	logistic_reg	— penalty — mixture	9
AD	3	rpart	decision_tree[2]	— cost_complexity — tree_depth — min_n	18
SVM	3	kernlab	svm_rbf	— cost — rbf_sigma	9
KNN	3	kknn	nearest_neighbor	— neighbors — weight_func — dist_power	27
RM	3	glmnet	multinom_reg	— penalty — mixture	9
BA	3	ranger	rand_forest[3]	— min_n — trees	6
XGB	3	xgboost	boost_tree[3]	— learn_rate — trees — tree_depth	18

Standard Logistic Regression (LR). This model is based on adjusting the β coefficients to minimize the difference between estimated probabilities and the actual observed values (Eq. 4):

$$P(Y = 1|X) = \frac{1}{1+e^{(-\beta_0+\beta_1 x_{i1} \cdots \beta_n x_{in})}} \quad (4)$$

$\boldsymbol{\beta_n}$ = Coefficient of parameter *n*.
$\mathbf{x_n}$ = Value of predictor *n*.

[2] Only archetypes with *tree_depth* > 1 are selected.
[3] Only archetypes with *trees* > 1 are selected.

Decision Tree (DT). These are supervised learning algorithms whose decision-making process is sequential -that is, it follows a specific order and hierarchy- and considers the characteristics of the input data for classification.

The process starts at a root node, which applies the first split condition to the dataset. Each subsequent decision node partitions the data based on specific attributes, and the branches represent the possible outcomes of each condition. It ends in leaf nodes, which contain the final predictions: discrete classes for classification problems or continuous values for regression.

For the establishment of the tree, in the case of classification issues specifically, metrics based on entropy are used (Eq. 5):

$$H(X) = \sum_{i=1}^{n} p_i \log_2(p_i) \tag{5}$$

H(X) = Entropy function of dataset X.
p_i = Proportion of examples of class i in the set X ($0 \leq p_i \leq 1$).

Support Vector Machines (SVM). Define a hyperplane in an n-dimensional space (being a line in a two-dimensional space or a plane in a three-dimensional space) that maximizes the margin between two distinct categories, that is, the distance between the hyperplane and the closest data samples –the fire records– from each class, defined as the support vectors (Eq. 6):

$$maximize \frac{2}{\|w\|} subject\ to\ y_i(w^T x_i + b) \geq 1 \tag{6}$$

w = Weight vector
T = Transposition of the vector or matrix.
x_i = Feature vector of observation i.
y_i = Label or category of observation i ($y_i \in \{-1,1\}$).
b = Bias term

The final classification is based on the calculation of the observation's distance to the hyperplane, specifically on the sign (positive or negative) of that distance.

k-Nearest Neighbors (KNN). This algorithm classifies an observation based on the training data that are closest (nearest neighbors) to it within an n-dimensional feature space. A parameter $k \in \{\mathbb{Z} > 0\}$ can be defined to determine the number of neighbors considered in the final decision-making process. It relies on distance metrics to calculate the closeness between points, with a common example being the Euclidean distance (Eq. 7):

$$d(x_i, x_j) = \sqrt{\sum_{k=1}^{n} (x_{ik} - x_{jk})^2} \tag{7}$$

x_i, x_j = Feature vectors of observations i and j.
n = Number of features or predictors.

Multinomial Regression (MR). This is a direct extension of linear regression that allows modeling nonlinear relationships between dependent and independent variables by introducing polynomial terms. It fits a curve to a specific dataset.

A polynomial is a mathematical expression that sums terms in which an independent variable x is raised to various powers, also referred to as degrees. In general, a polynomial of degree n is expressed as (Eq. 8):

$$y = \beta_0 + \beta_1 x_{i1} + \beta_1 {x_{i1}}^2 + \beta_1 {x_{i1}}^3 \dots \beta_n {x_{in}}^n \quad (8)$$

$\boldsymbol{\beta_n}$ = Coefficient of parameter n.
$\mathbf{x_n}$ = Value of predictor n.

The resulting model maintains linearity with respect to the parameters β, allowing the algorithm to apply the same techniques used in ordinary linear regression to fit the prediction model.

Random Forest (RF). Its structure is based on multiple decision trees -hence the name forests- which are trained to generate individual predictions that are then aggregated to produce a final overall prediction.

One of the core principles for achieving robust modeling is the introduction of randomness to reduce bias, typically drawn from two main sources: a Bootstrap Aggregating (Bagging) algorithm or a random selection of features. Similar to decision trees, Random Forest models are built using splitting criteria and entropy-based measures (see Eq. 5).

Extreme Gradient Boosting (XGBoost). An advanced implementation of gradient boosting that combines multiple weak learners to sequentially build a stronger model. It is specifically optimized for flexibility, efficiency, and accuracy.

It is trained sequentially using decision trees. In each iteration, the model is adjusted to predict the errors made by the previous model (Eq. 9):

$$F_{m+1}(x) = F_m(x) + \gamma \cdot h(x) \quad (9)$$

$\mathbf{F_m(x)}$ = Model at iteration m.
$\mathbf{h(x)}$ = Tree fitted at the current iteration to correct the residuals of $F_m(x)$.
$\boldsymbol{\gamma}$ = Learning rate ($0 \leq \gamma \leq 5$).

A *logarithmic loss function* is optimized using gradient descent (Eq. 10):

$$L(y, \hat{y}) = \sum_{i=1}^{n} \ell\,(y_i, \hat{y}_i) + \sum_k \Omega\,(f_k) \quad (10)$$

$\mathbf{L(y)}$ = Total objective function.
$\boldsymbol{\ell}\mathbf{(y_i)}$ = Loss function for observation i.
$\mathbf{\Omega(f_k)}$ = Regularization term for tree f_k (see Eq. 11).

This regularization term prevents overfitting on the training data, as defined (Eq. 11):

$$\Omega(f_k) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2 \quad (11)$$

$\boldsymbol{\gamma}$ = Penalty for the number of leaves T in the tree ($\gamma \geq 0$).

w_j = Weights of the leaves.
λ = Regularization coefficient that penalizes the magnitude of w_j ($\lambda \geq 0$).

2.5 Training and Evaluation of Submodels

The constructed datasets are split into 70% for training the base models and 30% for testing. Additionally, a *k-fold* cross-validation algorithm (k = 10) is applied to the training subset in order to select the best-performing submodels based on various statistical metrics (see Table 2).

Table 2. Statistical Metrics for Evaluation and Selection of the Best Submodels.

Statistic	Formula[4]
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
Precision	$\frac{TP}{TP+FP}$
Sensitivity	$\frac{TP}{TP+FN}$
F1-Score	$\frac{2 \cdot Precision \cdot Sensitivity}{Precision+Sensitivity}$
Kappa	$\frac{2 \cdot (TP \cdot TN - FP \cdot FN)}{(TP+FP) \cdot (FP+TN)+(TP+FN) \cdot (FN+TN)}$
Matthews Correlation Coefficient	$\frac{(VP \cdot VN - FP \cdot FN)}{\sqrt{(VP+FP) \cdot (FP+VN) \cdot (VP+FN) \cdot (FN+VN)}}$

2.6 Feature Importance

Gain. The individual contributions of each predictor to each model are evaluated through a feature importance permutation metric. This technique estimates the importance (gain) of each variable in a trained model by calculating the change in model performance when predictor values are randomly assigned.

2.7 Construction and Application of the Metamodel

The prediction results are generalized through a logistic regression metamodel (Eq. 12-13):

$$p_i = \frac{1}{1+e^{(-z_i)}} \tag{12}$$

p_i = Probability that an event belongs to a category, in this case, a fire-prone area ($0 \leq p_i \leq 1$).
z_i = Linear combination of the predictors (see Eq. 14).

[4] *TP = True Positives*; *TN = True Negatives*; *FP = False Positives*; *FN = False Negatives*.

$$z_i = \beta_0 + \beta_1 x_{i1} \ldots \beta_n x_{in} \tag{13}$$

β_n = Coefficient of parameter *n*.
x_n = Value of predictor *n*.

This algorithm is fitted by maximizing the likelihood, selecting the coefficients (β) that provide the best fit for the observed data (Eq. 14):

$$\ln L(\beta) = \sum_{i=1}^{n} [y_i \ln(p_i) + (1 - y_i) \cdot \ln(1 - p_i)] \tag{14}$$

L(β) = Likelihood function.
y_i = Dependent variable or label of observation *i* ($y_i \in \{0, 1\}$).

The addition of the Least Absolute Shrinkage and Selection Operator (*Lasso*) technique is considered, enforcing the sum of the absolute values of the coefficients (Eq. 15):

$$\lambda \sum_{j=1}^{p} |\beta_j| \tag{15}$$

λ = Regularization/penalty parameter.

Therefore, the process is given by (Eq. 16):

$$\hat{\beta} = \underset{\beta}{\operatorname{argmin}} \{ -[\sum_{i=1}^{n} (y_i \ln(p_i) + (1 - y_i) \cdot \ln(1 - p_i))] + \lambda \sum_{j=1}^{p} |\beta_j| \} \tag{16}$$

$\hat{\beta}$ = Vector of estimated coefficients.
argmin = Argument of the minimum coefficients.

This process regularizes and selects the variables more effectively, minimizing the risk of overfitting and improving the model's interpretability.

Finally, the logistic regression algorithm enables the classification of fire-prone areas based on the geospatial variance of the same predictors considered in the base models (Fig. 2).

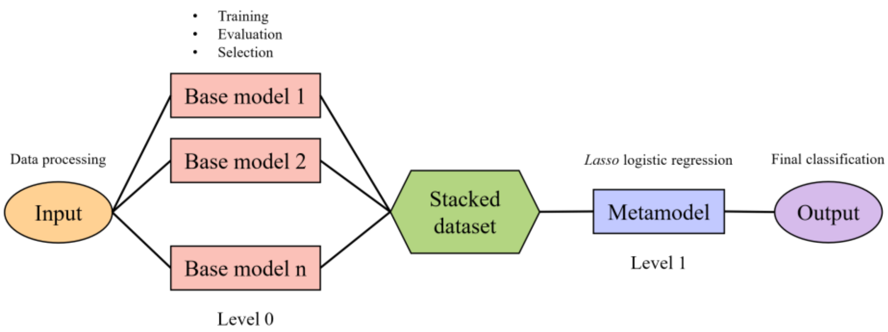

Fig. 2. Construction Process of Base Algorithms and the Metamodel for Classification.

3 Results

3.1 Fire Incident Records and Databases

Considering the selected time range from 2013 to 2022, a total of 4,694 confirmed fire records were identified between the months of February and May, varying in intensity, within the CMNP region (Fig. 3).

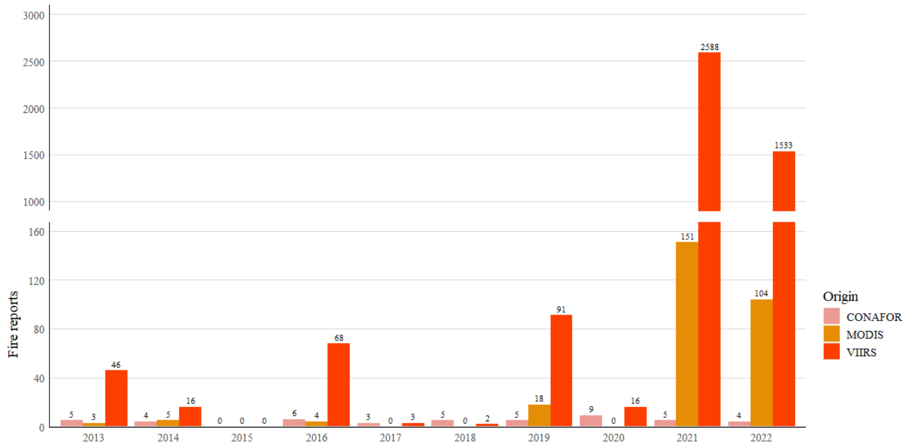

Fig. 3. Fire reports within CMNP from 2013 to 2022.

The analysis for the years 2015, 2017, and 2018 was excluded due to the insufficient availability of data to establish any modeling archetype ($n < 10$), thus rendering the modeling process impractical. From the 4,694 records collected from the SPPIF and FIRMS catalogs, seven databases corresponding to the years considered in the study were generated (Table 3).

Table 3. Data arrangement for each database is constructed annually.

Year	Occurrences	Pseudo-absences	Total
2013	54	54	108
2014	35	35	50
2016	78	78	156
2019	114	114	228
2020	25	25	50
2021	2 744	2 744	5 488
2022	1 641	1 641	3 282

3.2 Base Models and Submodels

Machine learning algorithms demonstrated their effectiveness in classification tasks, as evidenced by the performance evaluation metrics (Fig. 4).

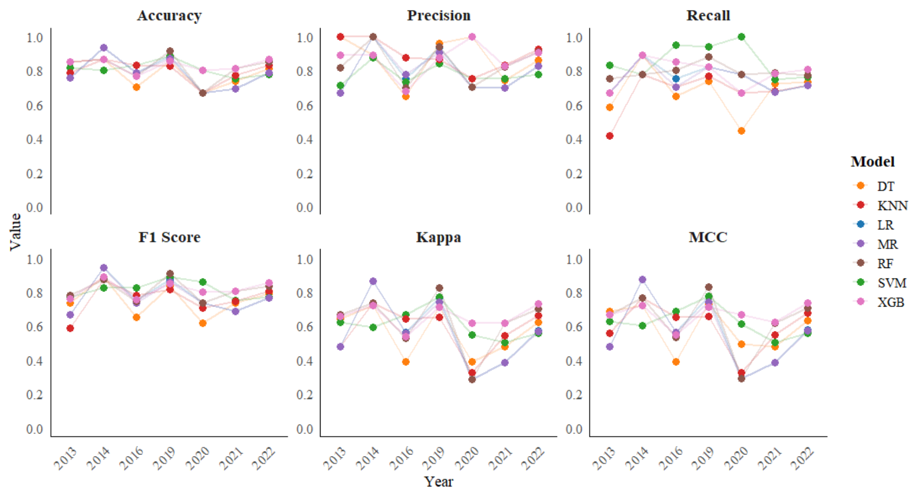

Fig. 4. Temporal dynamics of model performance.

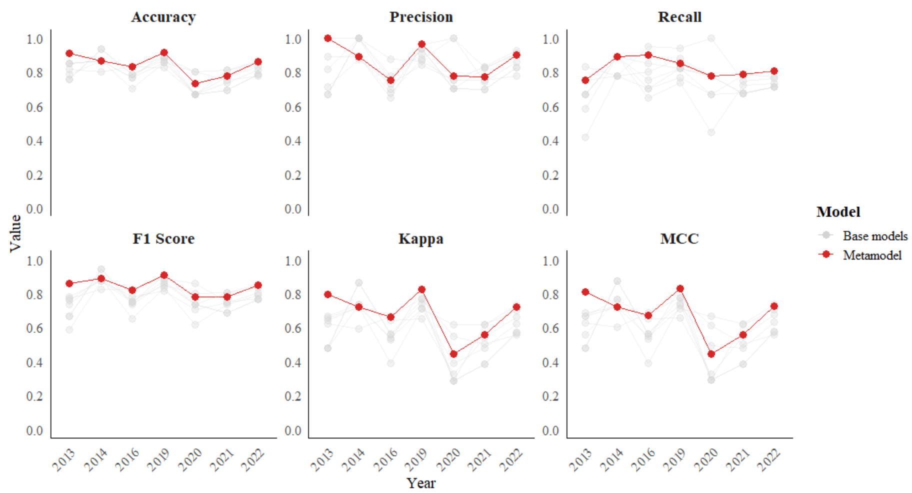

Fig. 6. Evaluation results of the constructed metamodels.

3.3 Predictor Importance

Regarding the relevance of predictors for the classification potential of the trained base models -and consequently the metamodels- the results of the permutation importance method applied for each year are presented (Fig. 5).

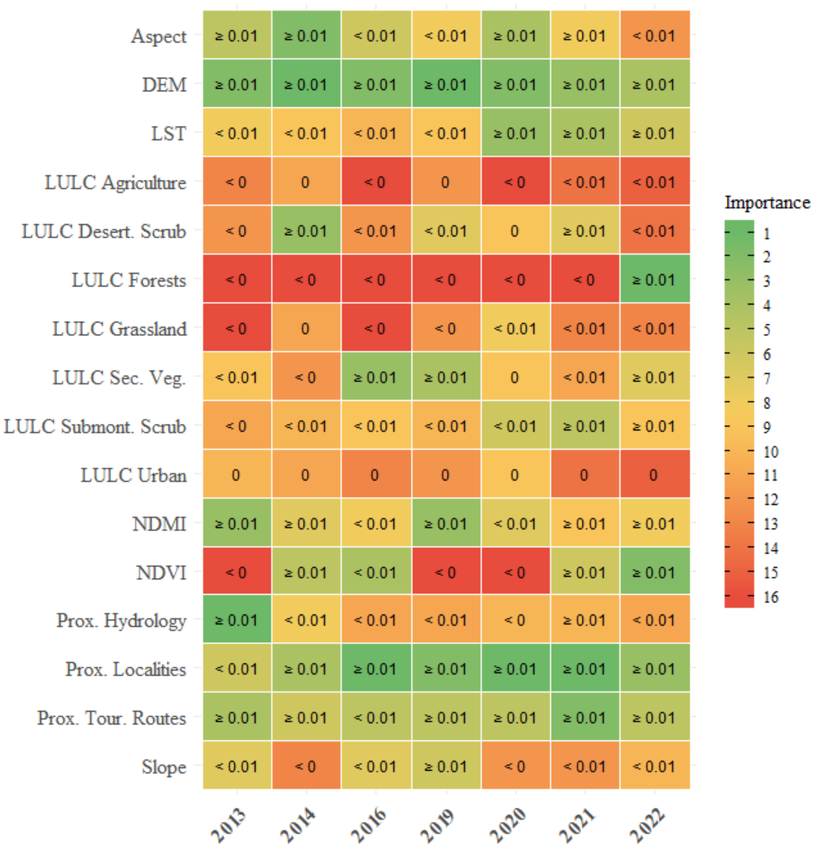

Fig. 5. Temporal dynamics of predictor importance used in the model structures. Where: DEM = Digital Elevation Model; LST = Land Surface Temperature; LULC = Land Use Land Cover; Sec. = Secondary Vegetation; NDMI = Normalized Difference Moisture Index; NDVI = Normalized Difference Vegetation Index.

3.4 Metamodels

Coefficients. Comparative analysis of the models (Table 4) shows a recurring pattern in which, during some stages, the influence of certain algorithms (such as Logistic Regression, Multinomial Regression, and Random Forests) is minimized or nullified (coefficients equal to 0), while others (Support Vector Machines, Extreme Gradient Boosting, and k-Nearest Neighbors) are favored with higher coefficients.

However, in specific periods, the metamodel incorporates all base algorithms, albeit with unequal weightings. Overall, there is a trend of preference for advanced techniques (such as XGB and SVM) over classical models (Logistic/Multinomial Regression), adjusting their influence according to the evaluated design.

Table 4. Determination of coefficients for the establishment of the metamodels.

	Coefficient							
Year	Intercept	RL	AD	SVM	KNN	RM	BA	XGB
2013	-1.05	0.00	0.36	0.95	0.18	0.00	0.18	0.44
2014	-1.50	0.00	0.31	0.81	0.30	0.69	0.01	0.94
2016	-2.02	0.00	0.65	1.48	0.63	0.00	0.00	0.76
2019	-2.38	0.24	0.72	0.93	0.55	0.49	0.64	1.08
2020	-2.25	0.49	0.08	1.34	0.83	0.89	0.00	0.50
2021	-1.55	0.00	0.19	0.54	0.64	0.00	0.55	0.94
2022	-2.04	0.14	0.34	0.53	0.64	0.15	0.59	1.08

Evaluation. Over the years, the metamodel has shown fluctuating performance relative to the base algorithms, reflecting both advancements and limitations (Fig. 6). Although the metamodel has evolved toward greater classification efficiency, its performance remains relative, depending on the integration capability of the base algorithms and its direct competition with more powerful methods.

3.5 Spatial evaluation

The categorized susceptible territory shows a spatially homogeneous distribution in the region, suggesting that wildfire occurrence probability may largely be attributed to stochastic events. However, starting in 2016, clusters of high susceptibility become evident in the central area of the region (Fig. 7).

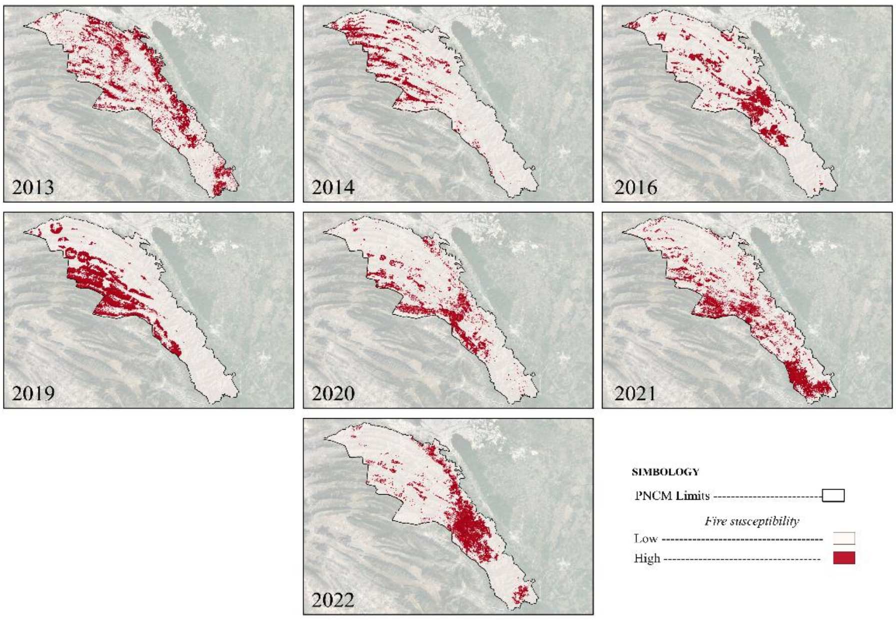

Fig. 7. Wildfire susceptibility within the CMNP.

Similarly, it is possible to identify specific territorial areas susceptible to wildfires during the different established periods (Table 5).

Table 4. Extent of wildfire-susceptible areas within the CMNP during each period.

Year	Susceptible area (km^{2})
2013	422.42
2014	228.57
2016	261.19
2019	354.04
2020	252.47
2021	387.47
2022	320.66

4 Discussion

4.1 Methodological Innovation

This research addresses the methodological challenge of non-integrative application of machine learning models, where the individual deficiencies of each model type are often highlighted (Nguyen *et al*., 2021; Kondylatos *et al*., 2022; Xie *et al*., 2022). This is achieved by constructing metamodels that integrate multiple Machine Learning algorithms to evaluate and predict the occurrence of wildfires for each year. These metamodels simultaneously incorporate LR, DT, SVM, KNN, MR, RF, and XGBoost algorithms, allowing for the creation of highly specialized classification models.

To logically classify regions with high susceptibility to wildfire occurrence, it is essential to rigorously select the predictors used to train the model (Reichstein *et al*., 2019; Jain *et al*., 2020). In most cases, this selection is empirical, which minimizes the possibilities of a correct analysis of the factors influencing the occurrence of wildfires, as it does not allow the evaluation of new and different predictors (Jain *et al*., 2020). For example, few studies incorporate demographic predictors (Kondylatos *et al*., 2022), which overlooks the anthropogenic impact on fire occurrence in natural regions, thus introducing a considerable bias when defining effective proposals for fire prevention and control. It is impossible to separate the human attributes that interact with the landscape (Likens, 1991; Western, 2001). A secondary finding of this study, resulting from the inclusion of such predictors in the training of models, is the identification of the temporal dynamics of the importance of specific predictors over the years.

4.2 Precision of Results

The developed metamodels allow for precise categorization of wildfire risk in the "Cumbres de Monterrey" National Park, with predictive accuracy varying across the years, reaching 91.30% in its best performance in 2019. These results enable the identification of high-vulnerability areas, promoting the implementation of appropriate prevention and response strategies.

However, it is necessary to mention that the model's accuracy varies over time, with reductions in 2020 and 2021 (73.77% and 77.90%, respectively). These variations could reflect changes in the quality and quantity of available data, such as the scarcity of fire records in certain years (e.g., 2015, 2017, and 2018).

This suggests the need for continuous improvement in the quality of training data and the tuning of model hyperparameters (Preeti *et al*., 2021), as these factors affect the models' ability to generate robust predictions depending on their inherent complexity (Brigato & Iocchi, 2021). Nevertheless, advanced techniques such as *k-fold* cross-validation and permutation-based feature selection ensure that the models are appropriately adjusted to the fire dynamics of the region (Tzu-Tsung & Po-Yang, 2020).

5 Conclusion

This study demonstrates the ability to characterize the territory of the CMNP through wildfire risk assessment using autonomous machine learning metamodels. The study underscores the need to coherently define temporal-spatial dimensions for any study based on its objectives, as this ensures the correct collection of predictor information for model training. Secondly, the integration of sufficient classification models -and iterations of these models- will increase classification accuracy. Lastly, rigorous analysis schemes must be developed for the interpretation of results without subjectivity.

The trajectory suggests that, while no single algorithm is universally superior, gradient-based and ensemble methods have the potential to redefine classification excellence standards. The methodology in this study can establish a technological innovation in addressing the wildfire problem in Mexico's natural regions, while simultaneously promoting the use of Geographic Information Systems (GIS), real-time spatial analysis, and autonomous Machine Learning methods for strategic planning in the control of environmental issues.

6 Declaration of interests

The author declares no financial interests or known relationships that may have influenced the work presented in this article.

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