CFMap: A Deep Convolutional Neural Network for Predicting Wildfire Risk Maps

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Keywords: Deep Learning, CNN, Wildfires, Fire Risk Map, CFMap, Machine Learning.

Abstract

Wildfires cause economic, social, and environmental consequences, as they affect ecosystems, public safety, biodiversity, and natural resources. They pose challenges to various world regions, particularly Mediterranean areas such as Spain. Numerous fire prediction and detection systems were introduced to detect and predict fires as well as prevent their risks and damage. Statistical methods and classical machine learning models were often employed to estimate and predict fire risk, showing their efficiency in generating fire risk maps. However, they fail to accurately capture complex temporal and spatial characteristics related to fire ignition. To address this challenge, a novel Convolutional Neural Network (CNN) model, namely CFMap, was introduced for predicting and generating detailed wildfire risk maps covering Spain regions. Comprehensive analyses were performed using data between 2008 and 2024, including fire history, geographical location information, land usage features, human activity indices, topography data, meteorological features, and vegetation indices from Spain regions, collected from the IberFire dataset. CFMap showed a superior performance with an accuracy of 0.8028 ± 0.0440, an AUC (Area Under the Curve) of 0.9354 ± 0.0088, and an F1-score of 0.7787 ± 0.0623, outperforming classical machine learning methods (XGBoost, LightGBM, and RandomForest) and deep learning models including ResNet and a simple CNN. These results demonstrate its reliability in predicting fire events and generating monthly fire risk maps for different Spain regions. Consequently, it helps to identify high fire risk zones, improve fire management strategies, and efficiently deploy firefighting resources, thereby reducing the potential risk and impact of fires.

1. Introduction

Wildfires are a frequent natural disaster affecting numerous regions of the world. They impact natural resources, ecosystems, economies, biodiversity, human lives, and ecological balance. In 2025, many regions faced extreme fire activity. For instance, Canada experienced a severe wildfire season with 5508 fires (until September), which burned more than 8.8 million hectares, representing 216% of the 10-year average (Canadian Wildland Fire Information System, 2025). European regions also recorded their worst fire season with a record of one million burned hectares, which represents half of Wales's land area. Spain and Portugal were particularly affected, together representing more than two-thirds of the total burned area in the European Union. Spain reported more than 400,000 burned hectares (until August), outperforming six times the average between 2006 and 2024, while Portugal registered a record of 270,000 burned hectares during the same period (Dawson and Rivault, 2025).

To reduce the impact and risk of fires, numerous methods were developed for predicting and detecting fire events as well as generating fire risk maps. Statistical methods and classical machine learning models such as logistic regression, XGBoost, multi-layer perceptron, SVM (Support Vector Machines), etc. (Tan and Feng, 2023, Shao et al., 2022, Mohajane et al., 2021) were employed. These methods showed an interesting performance, demonstrating their abilities in predicting fire risk maps. However, they fail to accurately identify the complex and non-linear spatial and temporal features generated from various data such as fire history data, geographical location information, human activity, topography data, vegetation indices, and meteorological features (Jiang et al., 2024, Zhang et al., 2019).

To address these challenges, numerous deep learning methods have been employed, showing their ability in detecting relevant and comprehensive features from heterogeneous and complex data and achieving high performance (Mambile et al., 2024, Ghali and Akhloufi, 2023b). As such, a novel convolutional neural network method, namely CFMap, was proposed in this paper to predict and generate fire risk maps across Spain regions. To train and evaluate CFMap, we used a large dataset, IberFire, which includes a high resolution spatio-temporal datacube specifically created for wildfire risk assessment in Spain (Ercibengoa et al., 2025b). This dataset consists of daily data at a 1 km $\times$ 1 km spatial resolution from 2008 to 2024, comprising 260 features such as meteorological conditions, topography features, land usage data, vegetation indices, fire history data, geographical location information, and human activity.

Two main contributions are introduced in this study:

- A novel CNN method, namely CFMap, was developed for generating and predicting monthly fire risk maps across Spain regions using complex spatio-temporal data, which includes numerous features such as vegetation indices, fire history data, geographical location information, human activity, meteorological conditions, topography features, and land usage data, helping to accurately identify fire risk regions.
- CFMap showed interesting performance better than classical machine learning and published deep learning methods. This confirms its reliability in predicting monthly fire risk maps. These maps can be used for various reasons, including firefighting operations to efficiently allocate resources and determine high risk zones. This improves decision making for firefighting, fire monitoring, and management strategies.

https://doi.org/10.5194/isprs-annals-XI-3-2026-173-2026

This paper is structured as follows: Section 2 reviews related works. Section 3 covers the materials and methods used, including the proposed method in section 3.1, evaluation metrics in section 3.3, and the dataset in section 3.2. Finally, section 4 presents the results and discussion.

2. Related works

Numerous methods were employed for predicting and generating wildfire risk maps, including basic statistical and probabilistic models, traditional machine learning methods, and deep learning approaches.

First, wildfire risk assessment was estimated using statistical methods and fire danger rating systems, such as the NFDRS system (National Fire Danger Rating System) of the United States and the CFFDRS system (Canadian Forest Fire Danger Rating System) (Júnior et al., 2022, Hanes et al., 2023). These systems daily estimate fire danger and the probability of fire ignition using humidity, wind direction and speed, temperature, precipitation, etc. They provided important decision support, improving wildfire control and prevention. However, these systems are still limited in generalizing to various fire scenarios as wildland fires have complex, varying, and unpredictable features (Pontes-Lopes et al., 2022). Additionally, they didn’t use important features such as human activity data and topography features, thus reducing their performance (Jiang et al., 2024).

To address these limitations, classical machine learning methods were employed for modeling complex environmental phenomena. Various models were implemented for mapping wildfire susceptibility including Random Forests, SVM, and Gradient Boosting Machines (e.g., XGBoost and LightGBM). These models demonstrated superior performance compared to traditional statistical methods, efficiently handling high dimensional data and learning complex patterns. For instance, Shao et al. (Shao et al., 2022) presented a comparative study of four classical machine learning models including gradient boosting decision tree, SVM, multi-layer perceptron, and Random Forest in predicting wildfire risk maps for China regions. Random Forest achieved high performance with an F1-score of 88.64%, an accuracy of 87.90%, and an AUC of 95.11% using numerous factors such as 17,330 active fires between 2012 and 2019, vegetation data, socioeconomic indices (population, special holiday, residential area, and road network), and meteorological information (temperature, sunshine hours, wind speed, humidity, air pressure, and precipitation), Topographic data (slope, elevation, and aspect). These results demonstrated the different seasons of the fire risk map across various regions of China, showing low risk in summer and fall and high risk in winter and spring. Mohajane et al. (Mohajane et al., 2021) introduced five hybrid models that combined a statistical method (Frequency Ratio (FR)) with machine learning algorithms (Multilayer Perceptron, Logistic Regression, SVM, Random Forest, and Classification and Regression Tree), to map fire risk in a Mediterranean area of Morocco. Experiments showed that the hybrid model Random Forest-FR achieved the best performance with an AUC of 0.989, closely followed by the SVM-FR model (AUC of 0.959). This demonstrates the ability of Random Forest model in processing large datasets and handling nonlinearities, while SVM showed its effectiveness in processing high dimensional data and preventing overfitting. Jaafari et al. (Jaafari et al., 2019) studied the ability of combined logistic regression and Dempster-Shafer methods to estimate the wildfire likelihood across Iran’s Zagros ecoregion. This method showed an improved AUC of 0.864 using 132 fire scenarios between 2007 and 2014 and twelve features such as distance to road, aspect, topographic wetness index, NDVI (Normalized Difference Vegetation Index), rivers, altitude, temperature, slope, rainfall, and residential areas. However, it failed in enhancing the probability of forest fire prediction. Ercibengoa et al. (Ercibengoa et al., 2025a, Ercibengoa et al., 2025b) presented a novel high spatio-temporal dataset at $1\ \text{km} \times 1\ \text{km} \times 1$ day resolution, namely IberFire, across Spain regions. It comprises data between 2008 and 2024, covering 260 features related to land cover data, human activity, meteorological data, geographic information, topography data, fire history, vegetation indices, and auxiliary features. The XGBoost machine learning method was tested on this dataset, and an AUC of 0.955 was achieved after data preprocessing, which included the exclusion of incorrect values and the generation of a balanced dataset with fire and non-fire scenarios.

Recently, deep learning models have been developed and have demonstrated high performance in different tasks, as they are able to handle very large and complex data and generate relevant and detailed features compared to classical machine learning methods (Tsirtsakis et al., 2025, Zhang et al., 2025, Ghali and Akhloufi, 2023a). Numerous architectures such as deep neural networks (DNNs) and CNN networks were employed for modeling complex environmental factors related to fire risk assessment. Naderpour et al. (Naderpour et al., 2021) used an optimized deep neural network to estimate wildfire risk in the Sydney’s Northern Beaches region. Experimental results performed using thirty-six features related to morphology, climate, topography, and human activity, achieving an AUC of 95.1%. Jiang et al. (Jiang et al., 2024) proposed a deep learning-based CNN method for forest fire risk assessment in China (Guangdong Province). They employed 11,507 historical fire events between 2011 and 2021, along with topographic (elevation, aspect, and slope), vegetation (land cover type and NDVI), weather (temperature, wind speed, humidity, and precipitation), and human activity (distance to road, distance to water, distance to places, population density, and gross domestic product density) data to train and evaluate their models. The proposed CNN achieved a superior F1-score of 84.9%, better than classical machine learning models such as Logistic Regression, Random Forest, SVM, KNN (K-nearest Neighbor), and Decision Tree.

Despite these advances, numerous challenges remain, such as the analysis of high resolution and multimodal spatio-temporal datasets to improve the prediction of fire risks. Additionally, many existing studies used a limited number of input features. Therefore, in this study, we applied a novel deep learning-based CNN method, namely CFMap, using publicly available IberFire datacube, which contains daily data (256 features) from 2008 to 2024 at a spatial resolution of $1\ \text{km} \times 1\ \text{km}$ across Spain regions to generate and predict monthly fire risk maps.

3. Materials and Methods

In this section, we first introduce our proposed CNN method, namely CFMap, for predicting fire risk maps. Then, we detail the IberFire dataset employed to train and evaluate this method with existing deep learning and machine learning models and the evaluation metrics (accuracy, AUC, and F1-score) used.

3.1 Proposed Method

We propose a deep learning method, namely CFMap, to predict wildfire risk maps. CFMap is a deep CNN method. It

https://doi.org/10.5194/isprs-annals-XI-3-2026-173-2026 |

includes two convolutional blocks to extract detailed and complex features. Each block consists of a convolutional layer with padding of 1 and kernel size of 3 followed by ReLU activation function, max pooling layer with kernel size of 2, and dropout of 0.3 to overcome overfitting. These two blocks extract low level and high level characteristics. Next, the generated feature maps are flattened and then passed through two fully connected layers. The first layer contains a dense layer with ReLU activation function, while the second consists of a sigmoid function to generate a binary output, representing the fire risk probability (between 0 and 1) for each spatial location and month.

Figure 1 introduces the proposed architecture for generating and predicting fire risk maps. First, numerous data preprocessing and feature engineering steps were employed to address missing data, ensure no duplicated time coordinates, and confirm that all feature values are corrected and conform to the logical and expected range of data. This process generated a balanced dataset of fire and non-fire scenarios and assured the quality and consistency of the input data, which includes heterogeneous and complex information. This facilitates the efficient training of the proposed model. Then, CFMap was used to predict the occurrence of fire events for each month and spatial unit as well as generate the predicted fire risk maps.

3.2 Dataset

IberFire dataset (Ercibengoa et al., 2025a, Ercibengoa et al., 2025b) is a publicly available data. It includes spatio-temporal data at 1 km $\times$ 1 km $\times$ 1 day resolution between December 2007 and December 2024, it was proposed to address the gap of detailed and localized data in Spain (not including Canary Islands, Mellila, and Ceuta). It consists of 256 features, covering topographic features collected from European digital elevation model (Eurostat, 2025), meteorological features from ERA5-Land (Copernicus Climate Change Service, 2025), fire history generated from the European Forest Fire Information System (European Commission, 2025), human activity collected from WorldPop (WorldPop, 2025), vegetation indices obtained from Copernicus Land Monitoring Service(Copernicus Land Monitoring Service, 2025a), auxiliary features to identify the cell, geographical location information, and land usage obtained from Copernicus Corine Land Cover (Copernicus Land Monitoring Service, 2025b). Table 1 reports the main and detailed features used on each category.

3.3 Evaluation metrics

To evaluate the performance of the implemented models, three standard classification metrics were used, including accuracy, AUC, and F1-score. These metrics provide a comprehensive assessment of the models' ability to accurately predict wildfire occurrences.

- Accuracy measures the proportion of all correct predictions including both fire and non-fire instances. It provides a general measure of the model's performance, as illustrated in Equation 1.

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{1}$$

  where TP, FN, FP, and TN represent true positive, false negative, false positive and true negative rates, respectively.

- AUC (Area Under the Curve) of the Receiver Operating Characteristic (ROC) curve is an important metric for evaluating a classifier's ability to distinguish between classes (fire and non-fire events in our case). It measures the model's performance across all possible classification thresholds.

- F1-score is the harmonic mean of precision and recall. It provides a single score that balances the trade-off between false positives (precision) and false negatives (recall), as presented in Equation 2.

$$F1-score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{2}$$

4. Results and Discussion

The implemented models (XGBoost, RandomForest, LightGBM, simple CNN, ResNet, and CFMap) were developed using Pytorch, and trained and tested on a machine with a RAM of 64 GB and a NVIDIA GeForce RTX 4090 (24 GB).

To train and test the proposed deep learning and machine learning models, we used the IberFire dataset, which includes fire history data, auxiliary features, land usage information, human activity data, topographic features, geographic information, vegetation indices, and meteorological data. Only fire and non-fire scenarios in Spain were selected for this study, according to the published study (Ercibengoa et al., 2025a), which employed XGBoost to predict fire risk maps in Spain, as it is the only work that used the IberFire dataset. We applied data preprocessing techniques to remove the missing data and duplicated time coordinates and to confirm that all values are corrected and conform to the logical and expected range of data. This step generated a randomly selected balanced data for the same dates, consisting of 139,316 instances (between 2008 and 2023) with 70,133 fire events and 69,183 non-fire events.

The following hyperparameters were applied during the training step: 100 epochs, batch size of 512, Adam optimizer, and learning rate of 0.001. In addition, a 5-fold temporal cross-validation strategy (TimeSeriesSplit) was used to evaluate the performance of the implemented machine learning and deep learning models on different periods. This strategy ensures that the methods used are always tested on data temporally following the data on which they were trained. This allows to prevent overfitting and verify the robustness and consistency of these methods, which is important for time series forecasting problems, especially for the fire risk prediction task. Binary cross entropy loss (CE) function was also employed to reduce the prediction errors and improve the learning performance of the proposed models during the training stage (see equation 3).

$$CE = -\frac{1}{m}\sum_{i=1}^{m}\left(x_j \log(\hat{x}_j) + (1-x_j)\log(1-\hat{x}_j)\right) \tag{3}$$

where $\hat{x}_j$ indicates the predicted output, x_j represents the existing label (non-fire and fire scenarios in our case), and m denotes the total number of samples used in the learning data.

The performance of the proposed CFMap was first evaluated using data between 2008 and 2023 with an analysis based on F1-score, AUC, and accuracy metrics. Then, it was compared with

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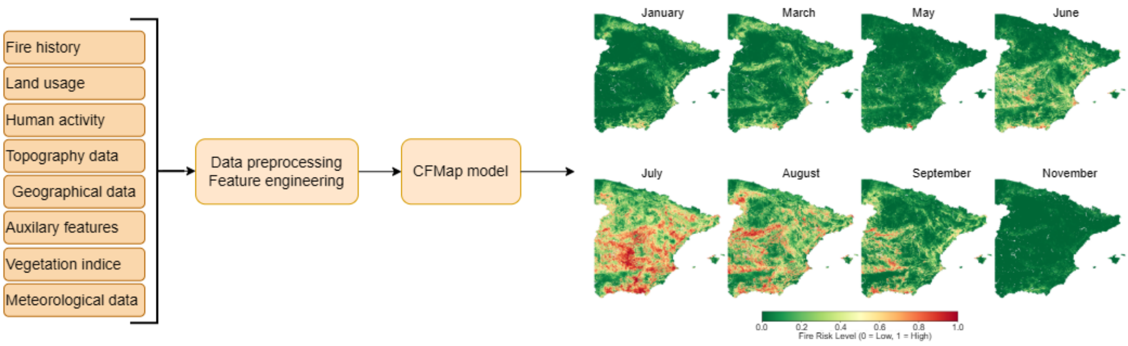

Figure 1. The proposed architecture.

Category	Feature description
Auxiliary features	x_index and y_index identify the grid cell; is_spain determines the Spain location;
Fire history	It illustrates the area burned during historical fires, with the start and the end of each fire;
Geographical location information	x_coordinate and y_coordinate indicate the geographic position of each event; is_waterbody and is_sea illustrate if the cell is located over inland water or open sea; AutonomousCommunities data presents the Nomenclature of Territorial Units for Statistics (NUTS) classification level;
Land usage	Label1, Label2, and Label3 indicate 44 categories of land cover classes in Europe;
Topography features	This category includes 9 features: 8 classes used to determine elevation, roughness, slope values, and aspect_NODATA feature to represent areas with no data available;
Human activity	It consists of 20 features generated from six explanatory variables related to human activity, including holiday periods, distance to railways, population density, distance to road, designation within the Natura 2000 protected network, and distance to waterways;
Meteorological feature	17 meteorological variables represent the factors that influence wildfire ignition and propagation, including the temperature, precipitation, wind speed and direction, relative humidity, and surface pressure;
Vegetation indices	Numerous indices were used such as Soil Water Index (SWI), Fraction of Photosynthetically Active Radiation (FAPAR), Land Surface Index (LST), Normalized Difference Water Index (NDVI), and Leaf Area Index (LAI). They determine the level of plant dryness, which helps predict fire risks;

Table 1. The main and detailed features of IberFire.

existing machine learning models (XGBoost, RandomForest, and LightGBM) and deep learning models (simple CNN and ResNet). Finally, the full 2024 data was used to predict the monthly fire risk map for the main regions of Spain, not including Canary Islands, Mellila, and Ceuta as no data were available for these regions.

Table 2 reports the obtained performance using 5-fold cross-validation. Our proposed model CFMap achieved superior results with an accuracy of 0.8028 ± 0.0440, an AUC of 0.9354 ± 0.0088 , and an F1-score of 0.7787 ± 0.0623 better than existing methods. Based on accuracy scores, it outperforms the classical machine learning models XGBoost, RandomForest, and LightGBM by 2.9%, 1.78%, and 5.71%, respectively. It also improves the accuracy by 6.05% and 0.99% compared to existing deep learning models, including ResNet and a simple CNN, which includes one convolutional layer followed by ReLU activation function, max pooling layer, and dropout of 0.3, respectively. This shows its ability in extracting comprehensive and detailed features for predicting fire. In addition, this performance demonstrates CFMap's reliability in detecting fire scenarios and reducing false alarms based on F1-score and its capacity to differentiate between fire and non-fire events based on AUC value. On the other hand, CFMap, LightGBM, simple CNN, and ResNet showed lower standard deviations (less than 0.1) among all used metrics, demonstrating their stability during the training step, while XGBoost and RandomForest achieved higher standard deviations, for example ± 0.1031 for XGBoost and ± 0.1032 for RandomForest, based on F1-score values. XGBoost and the simple CNN also obtained superior AUC of 0.9354 ± 0.0126 and 0.9307 ± 0.0129, respectively, while they reached lower F1-score (0.7240 ± 0.1031 for XGBoost and 0.7707 ± 0.0371 for simple CNN) compared to the proposed CFMap.

Figure 2 depicts the predicted fire maps using all 2024 data for the most relevant months (January, March, May, June, July, August, September and November), considering the varying fire seasons over the year in Spain. These predicted fire risk maps demonstrate great correspondence with fire history data. Furthermore, CFMap accurately predicted the seasonal evolution of the fire risk map, highlighting low probabilities in January, March, and November, high probabilities in June and September, and a peak in July and August due to dry vegetation, higher temperatures and lower humidity in Spain.

In summary, the proposed method CFMap obtained interesting performance based on accuracy, AUC, and F1-score metrics, outperforming classical machine learning methods and existing deep learning models. It demonstrates its ability in predicting fire events and in differentiating between fire and non-fire scenarios in different Spain regions. This shows its reliability and robustness in predicting monthly fire risk maps, which improves fire risk monitoring and strategies, as well as determining high risk zones. This optimizes firefighting resource allocation and monitoring efforts, helping firefighters respond efficiently and quickly during wildland fire events.

Model	Accuracy	AUC	F1-score
XGBoost	0.7738 ± 0.0542	0.9354 ± 0.0126	0.7240 ± 0.1031
RandomForest	0.7850 ± 0.0316	0.9238 ± 0.0176	0.7360 ± 0.1032
LightGBM	0.7457 ± 0.0802	0.8987 ± 0.0122	0.7068 ± 0.0489
simple CNN	0.7929 ± 0.0457	0.9307 ± 0.0129	0.7707 ± 0.0371
ResNet	0.7423 ± 0.0674	0.9050 ± 0.0073	0.6969 ± 0.0547
CFMap	$\mathbf{0.8028 \pm 0.0440}$	$\mathbf{0.9354 \pm 0.0088}$	$\mathbf{0.7787 \pm 0.0623}$

Table 2. Comparative analysis of the proposed models using IberFire dataset.

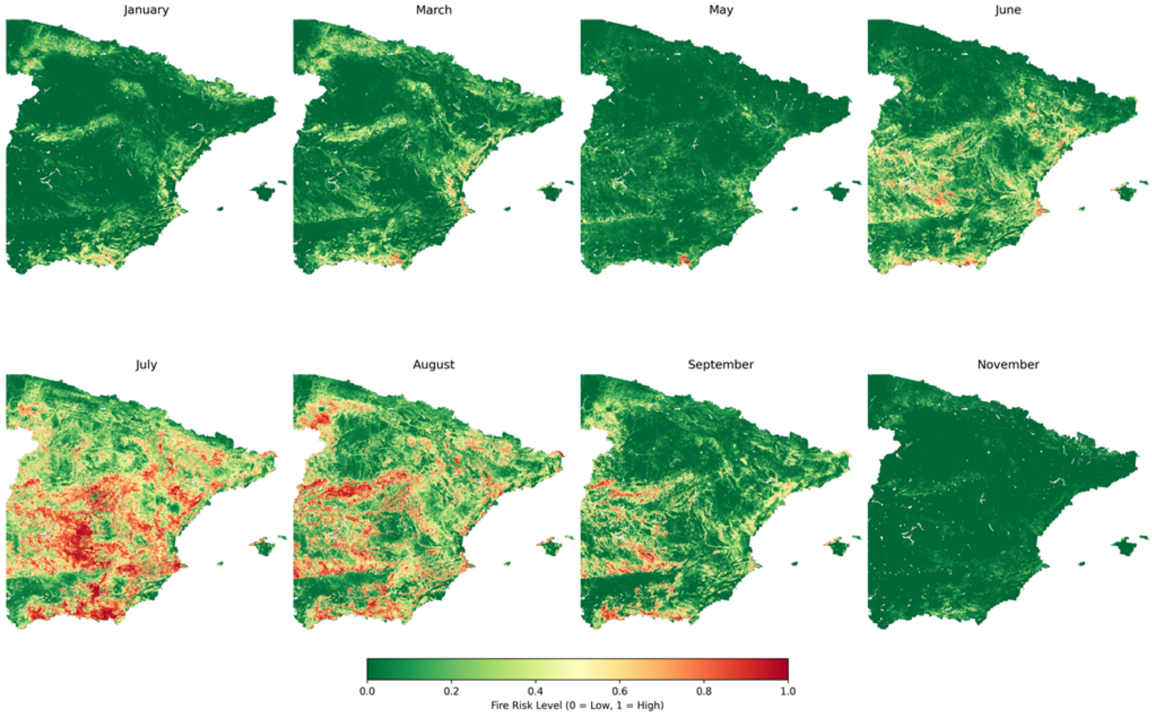

Figure 2. Fire risk map generated using the proposed model.

5. Conclusions

In this study, we presented a novel CNN method, namely, CFMap, to generate high resolution monthly wildfire risk maps for Spain regions. We used the publicly available IberFire dataset, which contains daily data from 2008 to 2024 at a spatial resolution of 1 km $\times$ 1 km across Spain regions to generate and predict monthly fire risk maps. IberFire consists of 256 features, including topographic data, meteorological features, fire history, human activity, vegetation indices, auxiliary features, geographic location information, and land usage data. Our proposed CFMap achieved the best performance with an accuracy of 0.8028 ± 0.0440, an AUC of 0.9354 ± 0.0088, and an F1-score of 0.7787 ± 0.0623 using a 5-fold temporal cross-validation strategy. It also outperformed classical machine learning methods such as XGBoost, RandomForest, LightGBM, and deep learning models, including ResNet and a simple CNN. This highlights the ability of CFMap in predicting fire risk maps that can be used for various purposes such as firefighting operations and determining high risk zones. This enhances fire monitoring and management strategies.

To enhance the potential and generalizability of our proposed CFMap, we first plan, as future work, to apply class imbalance techniques and collect a multimodal and high resolution data with numerous features similar to IberFire across North American regions (Canada and United States), as well as large scale climate factors such as El Niño. We will then train and test the CFMap method using both the new collected data and IberFire data to improve fire risk prediction performance.

Acknowledgements

This research was enabled in part by support provided by the Natural Sciences and Engineering Research Council of Canada (NSERC), funding reference number RGPIN-2024-05287.

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