Predicting wildfire events with calibrated probabilities

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This article addresses the challenge of predicting wildfires, a discrete event with a low occurrence frequency. Emphasizing the importance of model calibration for rare events, the study introduces a novel probability analysis method in the pre-processing stage. The dataset covers wildfires in specific French departments, providing a unique and unexplored perspective. The analysis considers the years 2015-2022 for training, testing, and validation, with 2023 serving as a generalization set. The local and precise nature of the dataset includes fires of all sizes and causes, distinguishing it from research focused on large-scale fires. Challenges include unknown fire causes, varying regional risks, and adapting to new data. The study aims to create a model predicting the probability of at least one fire occurrence on a given day, emphasizing the need for calibrated probabilities. The proposed method involves associating probabilities based on event proximity and training a regression model for calibration. The current results demonstrate a balanced approach between log loss and Expected Calibration Error.

CCS Concepts: • **Applied computing → Environmental sciences**; • **Computing methodologies**; • **Classification and regression trees**;

Additional Key Words and Phrases: Machine learning, Forecasting, Wildfire prediction, Probability calibration

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1 INTRODUCTION

Predicting discrete events is a crucial part of time series analysis. The objective is to predict the number of occurrences or the risk of occurrence of a particular event for a given time scale based on historical inputs [21]. This type of application is found in various domains, such as landslide prediction [11, 12], forest fire prediction [13, 15], road accidents [5, 16], medical diagnosis [30, 38]. Event prediction is a subset of discrete event prediction, characterized by the occurrence of events at a low frequency (< 10%), sometimes even very low (< 1%). This results in imbalanced databases, posing challenges for models to converge effectively. Additionally, proposed models often lack real-world applicability and generalization. Interpretability is also a common issue in understanding how models converge. These limitations have made the prediction of rare events a widely studied subject.

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This article focuses on predicting wildfires and introduces a novel probability analysis method in the pre-processing stage. The aim is to provide a better interpretation of results by proposing a model based on the probability of an event occurring on a given day, denoted as day J. Emphasis is placed on highlighting the need for calibration analysis in predicting rare events, where a risk value of 0.8 corresponds to an actual occurrence frequency of 80% [33]. This aspect is often overlooked in studies related to fire prediction. The dataset comprises records of wildfires in the departments of Doubs, Ain, and Yvelines. Recent climatic events have exposed these initially less-affected departments to increasingly dangerous and intense fire seasons. This dataset is unique and has not been analyzed before. The studied regions have unique particularities as they are in different location. The Yveline is a department located in the south of Paris with a population of 1,437 million. The Doubs is located in the North West of Swiss with a population of 539 465. The Ain is located in the South West of Swiss and North of Lyon with a population of 653 688, see Figure 1. Each department is unique considering the topography, population density or elevation. For instance the Yvelines is a a more populated department however it contains the forest of Rambouillet which is a important destination for tourism. The Ain contains much more mountains and small cities, the percentage of forest is also much higher. The Doubs is wetter than the other two, it helps us considering all type of department in order to analyse generalisation and adaptability

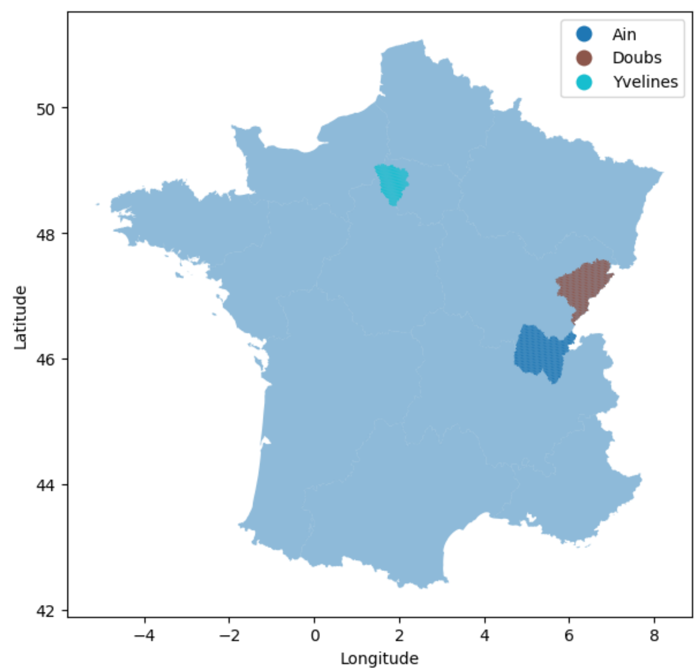

Fig. 1. **The locations of the departments Ain, Doubs, and Yvelines on the French territory**

The documented fires span from 2017 or 2018 to 2023, depending on the department (see Table 1). The study conducts an analysis of model generalization in real-world applications, considering the period 2015-2022 as the training, testing, and validation set, and 2023 as the generalization set. The 2023 set was not used in generating the weights and formulas during training. One particularity of our dataset is its local and precise nature, as we consider fires of all sizes and causes. This is in contrast to a significant amount of research that focuses on large-scale fires.

Table 1. **Distribution of fires in all departments.**

Departments	First Fire	Last Fire	Number
Ain	2018-01-05	2023-09-11	2654
Doubs	2017-06-05	2023-09-11	1892
Yvelines	2017-06-05	2023-09-11	2375

The ultimate goal of this study is to develop a model predicting the probability of a fire starting each day in different regions, with a focus on a one-day timescale, representing the risk of a fire starting in the region from 12 p.m. The models incorporate meteorological, topographical, and socio-economic variables, particularly utilizing the Fire Weather Index (FWI) [42] method, a reference in fire risk analysis. However, the drawback of this statistical method is its lack of generalization across diverse regions and its failure to adapt automatically to new inputs. The indices calculated are determined at 12 p.m. for a prediction at 4 p.m.

The escalating frequency of these fires has profound economic, ecological, and human implications. Regions such as the Mediterranean have long been recognized as high-risk areas, as emphasized in prior studies [41]. Additionally, the ongoing global warming phenomenon has expanded the scope of these vulnerable regions, with Central Europe now being identified as a new inclusion. The rising occurrence of drought periods in this previously unaffected region has amplified the risk, extending the threat beyond its traditional boundaries [23]. Integrating artificial intelligence in this domain not only enhances predictive accuracy but also empowers fire and rescue services [27]. This technology enables them to be better equipped, facilitating swift and efficient mobilization to contain wildfires before they escalate. Developing such a predictive tool marks a crucial stride in protecting lives, communities, and invaluable ecosystems.

The prediction of wildfires in natural areas is often approached as a binary classification problem [14, 15]. However, this strategy is not optimal for two reasons: first it assumes that all fires in the dataset are equally important and have an equal chance of occurring, then results will highly depend on the non fire point generation method (the 0 class). One particularity of wildfires is that the probability of ignition varies depending on the temporal and spatial scale of the region. This means that a fire is not equally likely to occur during the fire season as it is during winter. A possible strategy to address this issue is to selectively consider only wildfires during the significant fire season. However, this approach may exclude important elements from the dataset and hinder continuous risk analysis. To generate reliable future risk assessments and achieve good generalization in the real world, it is essential to consider all available inputs. In this article we proposed a novel strategy for creating calibrated probability in the pre-processing step, meaning that we are transforming the discrete binary form into a continuous probability. Our method offers several advantages :

(1) It allows for the consideration of the probability of an event occurrence rather than a fixed occurrence.
(2) Our method enhances interpretability for real-world applications as the output is directly linked to the input probability.
(3) By creating a continuous risk over time, we ease the transition to a model that calculates risk for multiple correlated events.

The article is organized as follows: first, we will explore the strategies implemented worldwide for fire prediction. Then, we will analyze the selected features. We will present the pre-processing method for generating calibrated probabilities. Finally, we will analyze the results of the various deployed models.

2 STATE OF THE ART

As mentioned earlier, the prediction of fire risk is often modeled using a binary format. Multiple strategies exist for generating points in class 0, corresponding to non-fire points, where the risk is considered to be 0. The choice of rules is often linked to the desired output scale. We will consider that, for a specific scale (less than 1 km of resolution), we will use the spatial-based method that generates points randomly in the studied region, well-distributed from fire points [13, 34]. This method assumes that the positions of fire points are known and not noisy. The use of this output at a small spatial scale is often employed for creating susceptibility maps [35, 39].

The use of Convolutional Neural Networks (CNNs) is well-suited for this type of prediction because it allows considering a small region as input rather than just a single point [7, 44]. Models of this kind demand a large amount of data, and the use of a small spatial scale significantly increases the number of pixels considered, thereby reducing the temporal analysis frequency [43]. By reducing the spatial scale, we can create grids that facilitate clustering of fires. The use of this method emphasizes the temporal evolution of data more than the spatial evolution [17, 32].

This format is not unique to fire prediction, as there are also studies on landslide prediction that operate on a similar principle [11, 18] or snow avalanche prediction [26]. The regressive format is employed when aiming to predict the potential burned area of each fire, making it suitable for large-scale fires. However, this data is not often available for all fires and regions [6, 37]. Predicting the number of fires per day is also a research branch, but it implies using a dataset where the number of fires varies significantly [36]. For the sake of comparison, in our dataset, the quantile at 0.80 corresponds to 1 fire in a day while the quantile at 0.85 is for 2 fires.

To the best of our knowledge, no study has truly considered the aspect of probability calibration in risk prediction. The algorithm's output is often interpreted as a risk index rather than a probability of ignition. The studied dataset is often unique, like a region in China [20, 24] or the north of Portugal [4]. Furthermore, the fires used are typically large-scale but represent only a subset of all fires.

3 CONSIDERED FEATURES

In this study, the features are classified into three classes. The first class includes meteorological variables such as temperature, humidity, 24-hour precipitation, wind speed, and wind direction. Additionally, it incorporates indices used in the Fire Weather Index (FWI) method, namely fwi, isi, ffmc and daily severity rating. These meteorological variables are considered for the same day and their variations over one week (rolling average, gradient, minimum, and maximum). We used the Meteostat Python library to retrieve this information. The data was obtained over multiple grids encompassing each department and then interpolated to the desired scale, see section 4.1. The data was collected at both 12:00 PM (following thre Fire Weather Index) and 4:00 PM since the peak intensity occurs at 4:00 PM, see Figure 2.

The second class comprises topographical data, including NDVI (Normalized Difference Vegetation Index), NDSI (Normalized Difference Snow Index), NDMI (Normalized Difference Moisture Index), and NDWI (Normalized Difference Water Index). It also includes land cover data (percentage of pixels for each class). The satellite data was retrieved using the Google Earth Engine [22] library from two catalogs :Sentinel-2 [3] for Index and Dynamic World [10] for the landcover. All the images correspond to mosaic images, taken every 15 days since 2017-06-05. Each original image has less than 30% cloud cover. The mosaic operation allows the retrieval of an image without missing pixels and as recent as possible. Additionally, the dataset incorporates average, minimum, and maximum altitude values. This data comes

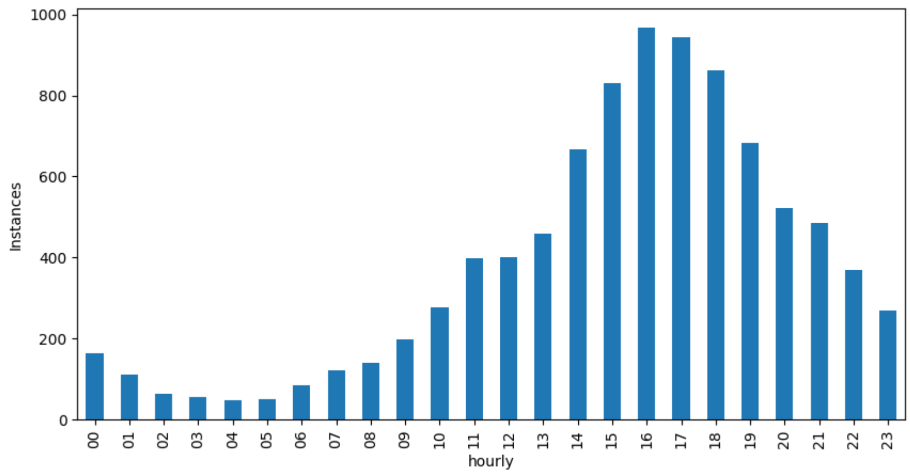

Fig. 2. **Distribution of fires throughout the day**

Clearly, there is an increase in the number of fires towards the end of the day. The purpose of collecting data at 12:00 PM and 4:00 PM is to predict this peak in time, enabling a quick and effective response to mitigate the impact.

from contour lines transcribed by the National Institute of Geographic and Forest Information (Institut national de l'information géographique et forestière or IGN in French) [1].

The third class includes socio-economic and calendar-based features, such as the average, minimum, and maximum population density, day of the week, day of the year, month, and holiday indicators. These diverse sets of features aim to capture the multi-faceted aspects influencing wildfire occurrence. The population density comes from the Kontur website. This database allows retrieving population density on hexagons at a 400m resolution [2].

4 PROPOSAL

4.1 Creating sub-regions

Our process begins by clustering each department into 10 sub-regions using the KMeans algorithm. The input data for clustering consists of the latitude and longitude positions of fires. This allows us to group fires together and consider the center of each cluster as a representative point for variable retrieval. It is important to note that clusters may vary in terms of the number of fires and their size. Consequently, we infer that the probability of a fire ignition varies according to the cluster. This step enables us to account for regions of different sizes, promoting generalization to new inputs, among other benefits.

4.2 Generate Calibrated Probabilities

Firstly, we disperse the number of fires over multiple days by applying a convolution with a Laplacian filter, cf. Fig. 3. Following this operation, we decrease the value for isolated fires but increase the values for days in proximity to the fires.

The second step involves calculating the sum of rolling averages over a series of temporal scales (7 days, 15 days, etc.) around each day, as in Eq. 1, in which J represents the day and T the maximum time scale (the number of days we want to consider). This enables us to capture both the global and local trends of fires. The larger the temporal scale, the

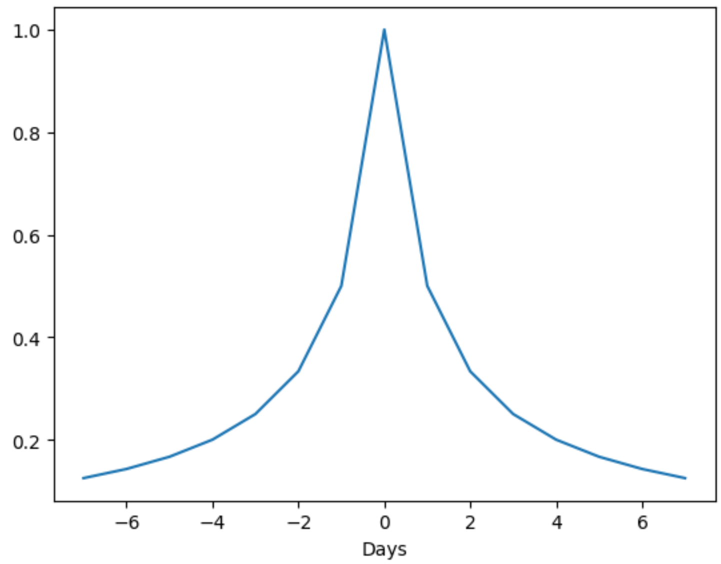

Fig. 3. **The Laplacian filter used for the diffusion of fires.**
The x-axis represents the number of days considered during the convolution, and the y-axis corresponds to the weight of the kernel.

more fires are considered, but beyond a certain threshold, it converges towards its limit. Our studies have shown that this limit is around 20 days.

$$\text{Influence}(J) = \sum_{t=1}^{T} \left(\frac{1}{2t+1} \sum_{i=-t}^{t} \text{Fires}_{J+i} \right) \tag{1}$$

In the continuation of these two steps, we obtain a continuous curve representing the fire intensity for each day. This value ranges from 0 to $+\infty$ and does not represent a probability. Additionally, each curve in each cluster has been generated individually and has no connection to the others. One possible transformation would be to apply a min-max scaling, but this only considers the individual value of each input. The solution implemented here is to apply logistic regression. This step resembles a typical post-processing calibration application. However, the input value is more precise than a probability calculated by a model because it considers both past and future events, which is not feasible in post-processing. Certainly, spatial information can be incorporated by using the cluster curve as input for logistic regression, along with the curves of the three nearest clusters. This implies that the risk also varies based on the situation of neighboring clusters. The quality of probabilities can be assessed using the Expected Calibration Error (ECE). Furthermore, one can calculate the log loss across the entire dataset and specifically on the days with fires to obtain a reference value.

An additional step involves clustering the obtained probabilities into classes. This step allows us to retrieve an explanatory class that can be used later. The algorithm used for this clustering was KMeans.

The Figure 4 depicts the calibration curves obtained on the 2015-2022 dataset across all regions. The evaluation of this curve occurs at several points. Firstly, the aim is to have probabilities covering the entire range between 0 and 1. Secondly, a desire for a relatively low ECE is present as it represents the overall quality of probabilities. Additionally, the evaluation can be performed on each bin or group of bins. The number of bins was calculated using the Freedman-Diaconis law [19]. In this case, it can be observed that the probability curve is well-defined across all values, with a reasonably reliable ECE (4.58% for 2017-2022 and 4.606% for 2017-2023). The quality of the bins depends on their average values. The best-calibrated bins are around 0.5, which is favorable as a probability of 0.5 indicates a 50% chance. The model tends to overestimate values above 0.5 and underestimate values below. Overall, the deviation is acceptable. However, a significant deviation is noted when the probability is around 0.05-0.1. This may be attributed to a too strong convolution in the initial part of the process. Note that the models have been trained only on the 2015-2022 dataset.

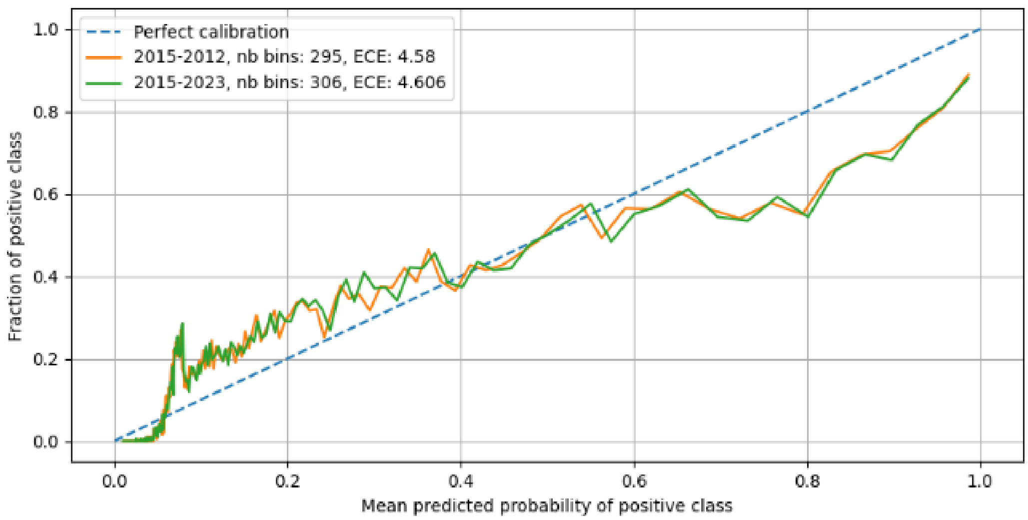

Fig. 4. **Calibration of probability**
On the x-axis, we find the calculated proportion of fires, and on the y-axis, the expected proportion of events. Each variation represents a different bin.

5 PREDICTION STAGE

5.1 Preprocessing

Note that some features (mostly topographic features from Sentinel 2 [3]) were only available after 2017-03-28, so after generating the probabilistic model, we only take the data belong this date. The imbalance in the database can pose challenges. After testing under-sampling and over-sampling algorithms such as SMOTE [8] and SMOGN [9], we found it more advantageous to retain the imbalance and adjust the weight parameters. Sample weights correspond to

$$w = \begin{cases} \frac{\text{Total\_c=0}}{\text{Total\_c}}, & \text{if } c \in 1,2,3,4 \\ 1, & \text{if } c = 0 \end{cases} \quad (2)$$

with c being the class generated by KMeans. Table 2 shows the weights calculated for each class. As can be seen, the weights increased according to the class risk. We calculated those weights in order to represent, in the training, *How many instances of a class for a 1 instance of the lower class* ?

Table 2. **Sample weights used in this study**

Class	Weights
0	1
1	5.6
2	13.8
3	22
4	25

5.2 Machine Learning

In this section we examine which input data format (continuous, binary) is most conducive to training. We have assembled a set of different state-of-the-art models based on their functionality and results. We choosed the so-called XGBoost, NGBoost, LightGBM, and Random Forest. Note that we plan to explore later some deep learning architectures [40, 45], and more specially the graph networks [25, 28, 29, 31].

5.3 Results

To evaluate our models, we use three different metrics. The logloss and fireLogloss (which is log loss calculated only on fire instance), for evaluating the probabilities calculated by the algorithm. Finally, the ECE assesses the calibration of the probabilities. Table 3 shows the performance of the algorithms. The period 2018-2022 corresponds to the test dataset, and 2023 is used to evaluate the generalization of the model. Models from the same category were trained with the same dataset and the same parameters. For NGBoost, we have tested different base learners, we found out that using XGBoost for regression and decision tree for classification brings the best results. When the ECE of binary models was high (greater than 8%), we applied sigmoid calibration.

Models with high ECE values tend to either overestimate or underestimate probabilities. Binary models show similar results, indicating an overestimation of probabilities. The results for the XGBoost and Random Forest models highlight a calibration issue in post-processing. A notable ECE discrepancy is observed for binary outcomes, with low log loss across all fires indicating a probability overestimation. While calibration reduces ECE, it significantly increases log loss across all fires, indicating the opposite effect of the original models. Upon examining the metrics of various regression models, it is evident that this format provides an alternative to the binary format. The regression models achieve a low ECE while maintaining a relatively acceptable log loss. This suggests that the regression approach offers a favorable balance between calibration accuracy and overall predictive performance compared to the binary format.

It is noticeable that the models adapt to the year 2023, but the metrics are slightly higher. It is observed that the models fall short of the results of the probabilistic model. Figure 5 shows some results on two clusters from the department of Ain: we can see that regression curve is less noisy and seems to fit better on the fire points.

6 CONCLUSION

The objective of this research was to develop a predictive model that estimates the likelihood of at least one fire incident occurring on any given day, with a particular focus on the calibration of these probabilities. Such a field of research presents several challenges. Firstly, the cause of fires is often unknown; although a significant majority is caused by human activities, they can be either accidental or intentional. Regions are not equal in terms of fire risk, and even those historically less affected are now facing longer fire seasons. Adapting to new data is crucial for real-world production. While this study focused on generalizing to a new year, models must also be able to adapt to new regions. The objective

Table 3. **Algorithms performance**

The log loss was calculated based on the weight of each sample. The weight of the test set corresponds to Equation 2.

Model	Version	2018-2022			2023		
		Logloss	FireLogloss	ECE	Logloss	FireLogloss	ECE
Probabilistic Model		0.54	0.71	4.58	0.55	0.72	4.6%
XGBoost	Binary	0.60	0.97	9.9%	0.64	1.04	11.13%
	sigmoid	0.79	1.59	2.7%	0.76	1.70	1.84%
	Regressive	0.63	1.12	2.27%	0.69	1.50	2.48%
LightGBM	Binary	0.64	1.16	5.1%	0.64	1.30	6.57%
	Regressive	0.64	1.08	3.26%	0.70	1.49	3.26%
Random Forest	Binary	0.60	0.93	12.95%	0.62	0.95	14.9%
	sigmoid	0.71	1.60	1.64%	0.74	1.63	1.26%
	Regressive	0.67	1.25	2.5%	0.67	1.54	1.9%
NGBoost	Binary	0.66	1.43	6.21%	0.65	1.45	7.74%
	Regressive	0.62	1.0	3.77%	0.63	1.26	4.686%

of our approach is to create a model capable of predicting, for the same day, the probability of at least one fire occurrence. This probability needs to be calibrated, meaning that a value of 0.8 corresponds to 80% of fires in the entire database. We have shown that binary classification models tend to overestimate the risk and create risks that are too high too often. The application of a logistic regressor helps calibrate the data but results in probabilities that are too low to accurately estimate the risk.

We have explored a method of generating calibrated probabilities in the pre-processing stage. Our method associates a probability with each event based on the presence of events of the same type in the vicinity. Training a regression model on these probabilities allows us to generate a calibrated risk without the need for post-processing calibration. The models strike a good balance between log loss and Expected Calibration Error (ECE). Although the results still lack precision, our next step will be to evaluate models related to deep learning. The recent release of Graphcast suggests that Graph Neural Networks (GNNs) offer promising results in time series prediction.

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7 DECLARATION

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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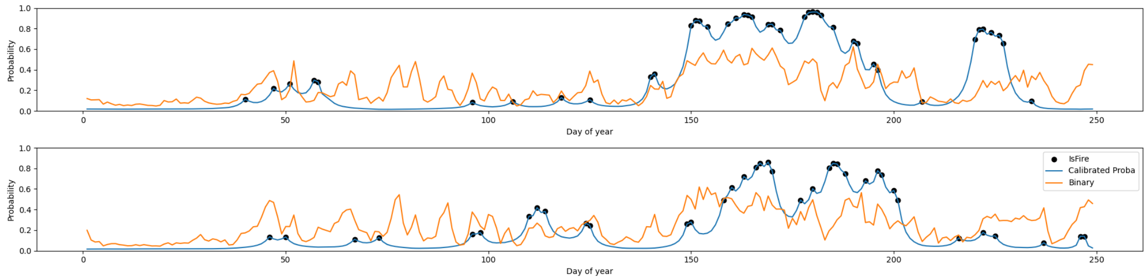
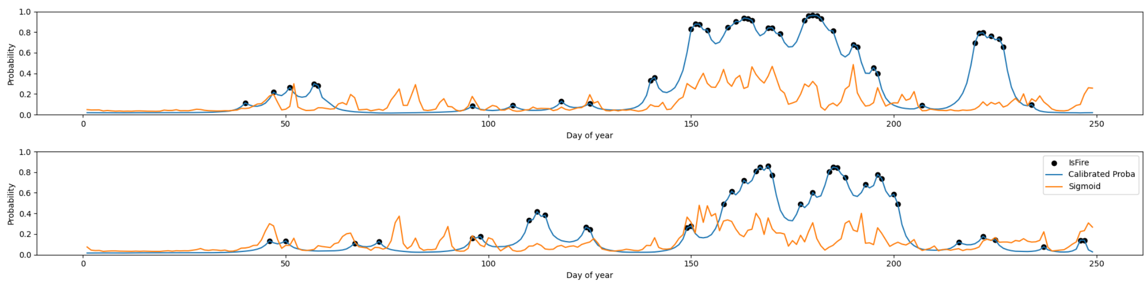
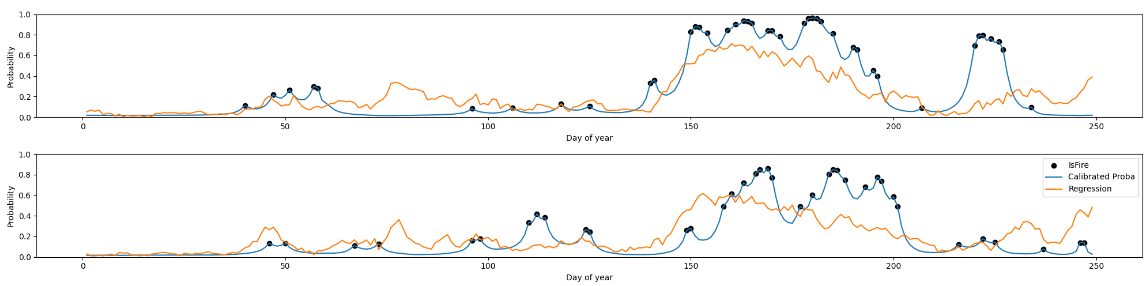


Binary without calibrator



Binary with sigmoid calibrator



Regression

Fig. 5. **Prediction Curve**

This figure represents prediction on two different clusters of the department of Ain for the year 2023. We can detect the high ECE from the binary curve without calibrator as it is much more changeable, the application of sigmoid seems to reduce the variation but the probability in the higher risk part seems to low. The regression output manages to achieve both a low variation curve and accurate probabilities.

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