River Levels Affecting Firefighter Interventions: Factor Analysis

Naoufal Sirri*
naoufal.sirri@univ-fcomte.fr
FEMTO-ST Institute, UMR 6174 CNRS
University of Franche-Comté, Belfort, France

Christophe Guyeux
christophe.guyeux@univ-fcomte.fr
FEMTO-ST Institute, UMR 6174 CNRS
University of Franche-Comté, Belfort, France

ABSTRACT

This research extends the continuum of studies exploring various variable categories and their implications for firefighters. The motivation stems from recognizing that river height, while it may impact the environment, is generally an immediate priority for firefighting interventions. Firefighters are primarily called for emergencies, prompting consideration of how river height, despite its environmental impact, could influence their operations. In this context, our investigation aims to comprehensively assess how river height influences firefighter interventions, with a particular emphasis on their frequency. The study's relevance is underscored by the significant impacts of flooding risks on the environment. Notably, in France, 23% of accidental drownings occurred in rivers, representing a major cause of death according to a public health survey in 2021, highlighting the critical nature of our research. Over nine years, from 2015 to 2024, our methodology encompasses data preparation, thorough analysis, and the application of the predictive XGBoost model, renowned for its speed and resilience to outliers. The iterative training pipeline selects features that improve the RMSE score over a 24-hour horizon, emphasizing the crucial importance of variables related to river height, particularly across all horizons. The main conclusion drawn from this study is that these variables exert an immediate and persistent impact on interventions, suggesting increased relevance for predicting outcomes over the entire duration. This precision in understanding models associated with the presence or absence of river flooding offers a practical approach to anticipate resource management, improve firefighter response times, and contribute to saving lives by mitigating intervention failures during major incidents. This study initiates a comprehensive exploration of variable families to understand the factors influencing firefighting activities.

CCS CONCEPTS

• **Computing methodologies → Machine learning**.

KEYWORDS

Firefighters intervention, Height of rivers impact, Feature selection, Intervention causes.

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1 INTRODUCTION

The influence of river heights on the frequency and nature of firefighter interventions, particularly in critical areas like the environment, is substantial. In France, accidental drownings represent a major cause of death, especially among individuals under 25 years old. An investigation conducted by "Public Health France" revealed that in 2021, 23% of accidental drownings occurred in watercourses, with a higher mortality rate (41%) compared to other locations [1]. However, harnessing river height surveillance data for specific event detection proves to be complex. The intricacies of spatial and temporal variability, coupled with the establishment of detection thresholds, require thorough analysis. This study aims to explore the potential correlation between river heights and firefighter interventions, thereby contributing to the development of more effective surveillance strategies.

In recent years, significant progress has been made in predicting river heights and firefighting interventions, thanks to the advancements in artificial intelligence and its applications. These developments have enabled researchers to enhance the accuracy and efficiency of prediction models, ultimately contributing to improved emergency response and risk management strategies.The study [26] developed a flood model using artificial neural networks (ANN) and geographic information systems (GIS) to simulate flood-prone areas in southern Peninsular Malaysia, with satisfactory results that can aid governments in future planning and infrastructure development. On the other side the study [27] compared the accuracy of three software computing methods artificial neural networks (ANNs), adaptive neuro-fuzzy inference system (ANFIS), coupled wavelet and neural network (WANN), and conventional sediment rating curve (SRC) approach to estimate daily suspended sediment load (SSL) at two gauging stations in the US, finding that WANN was the most accurate model in SSL estimation, with better performance than other models and the SRC method. In contrast, [24] estimated river bedform using Artificial Neural Network (ANN) and Support Vector Machine (SVM) methods, finding that the SVM model with RBF kernel function predicted bedform more accurately than other methods, with higher values of statistical parameters and better performance compared to empirical formulas and ANN. Additionally, [19] developed an efficient AI platform for real-time urban flood forecasting, integrating rainfall hyetographs embedded with uncertainty analyses as well as hydrological and hydraulic modeling, using deep learning for feature extraction and prediction, showing reliable results despite some inconsistencies. Moreover, recently the authors evaluated the use of support vector regression, long short-term memory, and their combination for river height prediction using historical sensor data, with LSTM-SVR showing better performance in capturing rapid transient changes in river levels [17]. [16] implemented data privacy using Differential Privacy (DP), employing a local differential privacy approach, while predicting firefighter interventions in specific locations from statistical estimators. Similarly, [18] applied natural language processing techniques to extract features from weather bulletin texts to predict peak intervention periods caused by rare events. Additionally, [23] demonstrated the feasibility of a continuously updated and optimized database using dedicated feature selection tools for XGBoost. Finally, in the same context as our paper, two studies were conducted to analyze the impact of specific features, namely air quality and solar activity, on firefighter interventions by [28] and [29], respectively.

Our research group tackles this issue by embracing an innovative approach: studying the influence of river heights on firefighter interventions. Leveraging rich historical datasets containing information on both river heights and firefighter interventions, we delve into this relationship. The main objective of this article is to assess the impact of river heights on firefighter interventions, focusing particularly on their frequency. To achieve this, we have formulated a hypothesis and its prediction within the scope of our research:

- Hypothesis: An increase in river heights will exhibit a correlation with a sustained rise in firefighter interventions from the outset.
  Prediction: The presence of elevated water levels is expected to systematically impact the environment, leading to interventions over a prolonged and sustained period.

To ensure a systematic and organized approach to our research, we meticulously developed and adhered to a methodological plan. In Section 2, we provide a comprehensive overview of the methods and materials utilized in the experiments, outlining our experimental approach. The research process and obtained results are presented in Section 3. Section 4 delves into an in-depth analysis and critical reflection on the findings, addressing the initial research question and emphasizing relevant implications and interpretations. The study concludes in Section 5, synthesizing the main conclusions, highlighting significant contributions, and suggesting potential avenues for future research. This methodological framework facilitated a systematic exploration of the correlation between of river heights and firefighting interventions while maintaining a holistic approach throughout our investigation.

2 METHODS

2.1 Data Preparation

2.1.1 Data Acquisition. This study utilizes an extensive dataset sourced from the Service d'Incendie et de Secours du Doubs (SDIS 25), France, encompassing 322,197 documented interventions spanning from January 1, 2015, to March 30, 2024. Each intervention entry is meticulously documented, comprising an identification code, precise start and end timestamps, geographical coordinates, intervention type, and response durations. Various contextual features were incorporated to comprehensively delineate incident circumstances. These encompassed meteorological parameters, solar activity metrics, river water levels within the Doubs department (French firefighters are responsible for various rescues, including floods), air quality indices, epidemiological statistics, holiday periods, lunar phases, and additional relevant factors. To prognosticate forthcoming intervention occurrences, a comprehensive dataset was curated by amalgamating firefighter intervention records with supplementary information from diverse sources. The process is detailed as follows:

- The key entries within the dictionary are organized into hourly segments, spanning from "01/01/2015 00:00:00" to "30/03/2024 18:00:00", formatted as "YYYY-MM-DD hh:mm".
- Data regarding the water levels of the initial forty rivers in Doubs were sourced from the governmental service "Hydroreel" and incorporated into the study. The process entailed populating a dictionary with the nearest average measurements for each hourly interval, as referenced in [5].
- To evaluate the influence of solar activity, features including 10 cm radio flux, sunspot count, sunspot area, and X-ray emissions were incorporated, as referenced in [9].
- To evaluate the influence of air quality, features including particulate matter ($PM_{2.5}$, PM_{10}), ozone (O_3), and nitrogen oxides (NO_2) from various air quality monitoring stations nearby, as referenced in [3].
- Data from NASA's VIIRS and MODIS satellites were continuously collected, capturing Earth images with diverse wavelengths and resolutions to analyze fire propagation in specific areas, as documented in [10] and [7].
- The [12] libraries were employed to compute the spatial separation among the Earth, Moon, and Sun. Utilizing Astral [2], various parameters related to the sun and moon, including moon phase and moonrise, were analyzed to assess their influence on natural calamities. Furthermore, sunrise and sunset data were utilized to establish a boolean variable signifying "night" or "day".
- Integration of weekly epidemiological data sourced from the Sentinelles network, encompassing ailments such as chickenpox, influenza, and acute diarrhea, as documented in [11].
- Incorporation of variables associated to French league and Champions League football matches, acknowledged as probable factors impacting interventions, as referenced in [13].
- Integration of temporal details encompassing time, day, day of the week, day of the year, month, and year, alongside information on holidays, academic breaks sourced from [6], and events like Ramadan observances, lockdowns, and curfews.
- Initially, our meteorological data reference was Météo France [8] (the french public meteorological service). However, difficulties arose due to access limitations to remote main stations and a three-hour sampling interval, which affected geographical and temporal accuracy. Despite Météo France bulletins offering information on diverse weather risks, the introduction of MeteoStat [4] was crucial in addressing this constraint. MeteoStat offers forthcoming forecasts, augmenting the functionalities of Météo France.

- Data retrieved from three meteorological stations in the Doubs department includes a comprehensive array of atmospheric metrics. These encompass atmospheric pressure, cloud cover, barometric trends, temperature, humidity levels, precipitation within the last hour, dew point, precipitation over the past three hours, gust speeds over a specified interval, average wind speed recorded at 10-minute intervals, horizontal visibility, average wind direction tracked every 10 minutes, and the prevailing climatic conditions, all sourced from Météo France.
- Collected MétéoFrance weather advisories encompassing diverse meteorological hazards such as wind, rainfall, floods, storms, snowfall, freezing rain, heatwaves, and extreme cold, each categorized with color codes (green, orange, red, yellow), augmenting the significance of the meteorological dataset [15].
- The MeteoStat API was used to access climatic variables such as temperature, dew point, precipitation, snowfall, wind speed and direction, pressure, and humidity sourced from openly available meteorological and climate datasets. Temperature data was extracted from an extensive 11x11 grid network spanning the entirety of the department.

The selected variables, derived from an examination of firefighter interventions, are designed to ascertain their potential influence. While this inclusive methodology poses the possibility of integrating non-significant variables, it enables the assessment of correlations between variables related to the heights of rivers and additional parameters. Encompassing various risks including accidents, fires, and floods, among others, these variables feature prominently in the dataset of firefighter interventions.

2.1.2 Data Pre-processing. During the data processing phase, linear interpolation was employed to handle missing values within certain meteorological datasets. To suit our learning model, two techniques from the Scikit-learn library [21] were utilized. The "StandardScaler" approach was implemented to standardize numerical features, encompassing variables such as year, hour, humidity, dew point, wind speed and direction, influenza, cloud cover, precipitation, gusts, visibility, varicella statistics, temperature, acute diarrhea, river levels, and lunar distance. This method adjusts the distribution of values to achieve a mean of zero and unit variance.

Additionally, we employed the "TargetEncoder" technique [14] to encode categorical attributes, including the day of the week, year, month, barometric trend, holidays, and events. This method transformed these variables by replacing each category with the mean of the corresponding target variable. We retained the original target values (the count of interventions) as discrete entities, as they better reflect the distribution of interventions.

2.1.3 Data Mining. A comprehensive examination of the dataset proved indispensable in extracting pertinent insights for our study. On average, there were approximately 30,000 interventions recorded per year, with a noticeable upward trend in intervention frequency over time. Concerning variables associated with river heights, Table 1 presents key statistical metrics for various river height parameters. It offers a concise summary of the central tendencies, variability, and observed distribution patterns across different categories of variables within this domain. Initially, data from 40 rivers within the department were collected, but only those situated in areas with a significant population density surrounding the river were retained. All these variables are represented as continuous entities, predominantly demonstrating a right-skewed distribution. However, two variables, Le_Doubs_de_Mouthe and La_Savoureuse_de_Giromagny, exhibit bimodal distribution patterns (refer to Figures 1 (a) and 1 (b)). In the context of temporal analysis, these modes may correspond to distinct seasons characterized by varying precipitation levels, implying a connection between river height fluctuations and seasonal weather patterns, geographical features like steep valleys or mountainous terrain, and human interventions such as dam constructions or alterations in river courses.

Moreover, the examination of these variables through time series analysis demonstrates a notable degree of similarity. To substantiate this observation, we conducted a correlation analysis among these variables, revealing findings that affirm the lack of localized variability while indicating significant correlations. These correlations span from 0.71 to 0.95, suggesting that these variables furnish redundant information for prediction, indicative of a shared influential factor. Consequently, these outcomes pivot our research towards a broader departmental outlook rather than a localized one, underscoring the absence of discernible localized effects.

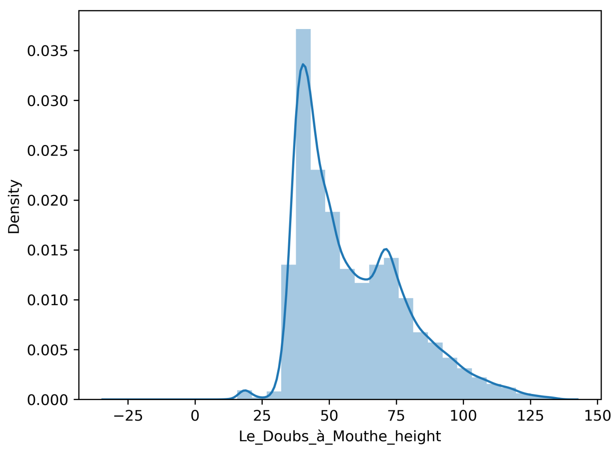
In concluding our analysis, we sought to assess the influence of river heights on both the overall target variable and specific categories thereof, employing a correlation analysis. The findings indicate a tenuous and statistically insignificant impact on the overarching target variable. However, a modest effect was discernible, particularly in the context of all river heights, demonstrating correlations ranging from 0.21 to 0.27 with a specific category of the target variable, namely floods. These insights offer preliminary glimpses into the constrained role of river heights in shaping intervention patterns. While notable correlations are absent, the prospect of a more intricate relationship underscores our comprehension of the nuanced interplay between river heights and incidents necessitating emergency services intervention.

2.2 Feature and Model Selection

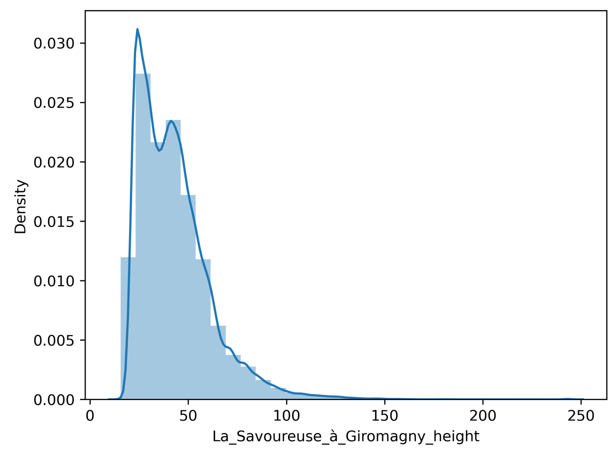
In the past, it was customary to incorporate all available features from the training dataset under the assumption that maximizing information inclusion would yield an optimal model. However, advocating for a constraint on the number of features considered arises from two principal reasons. Firstly, certain variables may display strong interdependencies, while others might contribute minimally to predictive capacity, potentially leading to diminished model generalization or the introduction of redundant information. Secondly, the inclusion of numerous features can substantially escalate computational complexity without commensurate enhancements in model performance [22]. Thus, employing a more restricted feature set holds promise for achieving more efficient outcomes. In this investigation, we employed the 'feature importance' method for feature selection, assigning scores to each variable in the dataset, with higher scores denoting greater relevance [30]. A threshold was

Table 1: Data analysis of river height variables (cm)

Variable	Mean	Std	IQR	Max	Distinct values
La_Bourbeuse	43.4	47.4	44.1	279.0	17,511
Le_Drugeon	45.5	35.8	46.4	1051.0	19,457
Le_Doubs_de_Mouthe	58.7	20.2	30.0	136.0	12,392
L'Allan	61.6	18.1	15.0	205.9	9,846
Le_Dessoubre	58.5	37.8	39.8	502.0	10,136
La_Savoureuse_de_Giromagny	43.1	18.6	23.1	245.0	11,461
Le_Doubs_canal_de_Besançon	235.7	69.4	70.0	2557.3	10,570
La_Rosemontoise	8.0	26.3	17.1	305.0	10,648
Le_Doubs_de_Labergement	33.9	29.7	32.0	191.7	15,557
La_Savoureuse_de_Belfort	20.9	18.5	23.0	147.9	10,961



(a) Distribution of Le_Doubs



(b) Distribution of La_Savoureuse

Figure 1: Analysis of the distribution of Le_Doubs_de_Mouthe and La_Savoureuse_de_Giromagny

established to retain the top 400 most pertinent features. Diverse selection techniques were applied, including:

(1) High Variance: preserving characteristics with variances exceeding 0.5.
(2) Pearson and Spearman correlation coefficients: filtering out correlations with the target variable whose absolute value equals or exceeds 0.4.
(3) Chi-Square Selector: applied the chi-square test to evaluate the association between each feature and the target variable after normalizing the features using the 'Min-Max Scaler' function.
(4) Extreme Gradient Boosting (XGBoost) [20]: employed preset hyperparameters (maximum depth = 7, number of estimators = 100000, early stopping after 10 rounds), conducted training, and subsequently calculated or obtained feature importance.
(5) Light Gradient Boosting Model (LightGBM) [25]: used specified hyperparameters (learning rate = 0.1, objective function = regression, metric = RMSE, number of leaves = 2^7, maximum depth = 7, number of estimators = 100000, early stopping after 10 rounds), and extracted feature importance as mentioned previously.

The culmination of this selection process yields a refined roster of features, prioritizing those consistently pinpointed by multiple techniques. From the initial pool of 3912 features, roughly 10% were preserved, culminating in a subset of 400 features employed for model training.

In our model selection process, we opt for Extreme Gradient Boosting (XGBoost) [20]. Renowned for its scalability, efficiency, flexibility, and speed, XGBoost is adept at navigating intricate datasets while achieving remarkable predictive accuracy. Its efficacy lies in its integration of gradient-boosting principles, allowing it to iteratively enhance the performance of weak learners. Widely embraced across diverse domains, from finance to healthcare, XGBoost exhibits versatility in addressing regression, classification, and ranking tasks with exceptional proficiency. Its popularity is underscored by its adeptness in handling missing data, feature selection, and adaptation to various data types.

2.3 Approaches Implemented for The Prediction Tool

To translate our theoretical analysis into practical application, we constructed a robust training and optimization pipeline (see Figure 2).

(1) We initiated numerous training iterations, covering various timeframes ranging from 1 to 24 hours, aiming to evaluate the influence of the height of rivers up to 24 hours in advance.
(2) Subsequently, we performed feature extraction as delineated in the "Feature Selection" section.
(3) Iteratively, each selected variable from the preceding phase was incorporated into the XGBoost model for training purposes.
(4) In each iteration, we partitioned the dataset into training, testing, and validation subsets. Initially, 20% of the data was allocated for testing, while the remaining 80% was designated for training-validation. Subsequently, we adjusted the allocation to 80% for training and 20% for validation.
(5) We conducted training for the XGBoost model, employing preset hyperparameters (see Table 2) and integrating early stopping with "early_stopping_
rounds=15". This mechanism was employed to halt training if there was no improvement in the performance on the validation set for 15 consecutive rounds. This decision was influenced by the fixed 100,000 estimators in our model.
(6) We calculated prediction scores using the RMSE metric (Equation 1) and compared them to previous scores. Variables that exhibited improvement were preserved in the input list via a sequential feature selection approach, and the preceding scores were accordingly adjusted.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{1}$$

(7) Finally, we embarked on an ultimate endeavor to fine-tune prediction outcomes by exploring various combinations of hyperparameters (see Table 3). This endeavor entailed the utilization of "early_stopping_rounds=25" alongside a fixed parameter set comprising 100,000 estimators. Through our iterative methodology, we identified optimal hyperparameter configurations, pinpointing a combination of values conducive to enhanced performance.

3 RESULTS

Substantial efforts have been dedicated to assembling, processing, and consolidating a comprehensive dataset, with a keen focus on amalgamating information from diverse sources of past interventions. Special attention was directed towards evaluating the significance of each variable within this framework. As articulated earlier, the essence of this study lies in unearthing pertinent insights regarding the impact of river heights on intervention forecasting. The preceding section delineated a methodology for identifying crucial features. Following the training of our model across a day-long timeframe, we present the outcomes of this feature selection process, honing in on river height-related variables whose inclusion led to enhanced prediction accuracy (refer to Table 4).

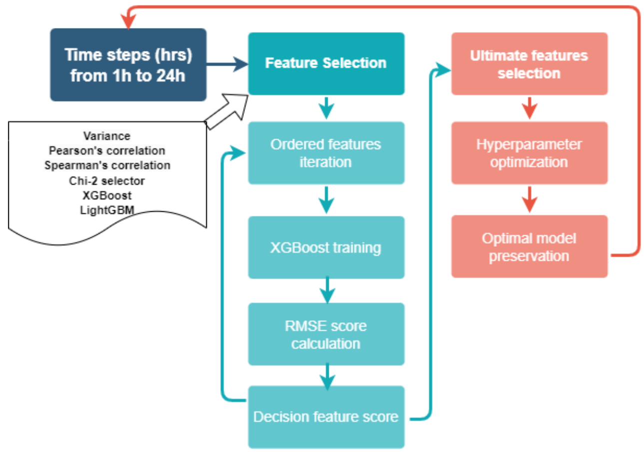


Figure 2: Training pipeline representation model

Table 2: XGBoost default hyperparameters

Hyperparameter	Values
max_depth	7
min_child_weight	1
gamma	0
subsample	0.8
colsample_bytree	0.8
learning_rate	0.1

Table 3: Settings XGBoost hyperparameters

Hyperparameter	XGBoost
`max_depth`	[2, 14]
`min_child_weight`	[0, 14]
`gamma`	[0.0, 0.4]
`subsample`	[0.6, 0.9]
`colsample_bytree`	[0.6, 0.9]
`learning_rate`	[0.01, 0.009]

Additionally, we present the classification outcomes yielded by our model, poised for interpretation in the subsequent section. Table 5 delineates the predictive efficacy of the XGBoost model concerning intervention counts, encompassing temporal horizons inclusive of river height variables, with the most notable performances accentuated in bold. Moreover, it outlines the RMSE metrics before and after the incorporation of river height variables, along with the percentage improvement. Figure 3 illustrates the outcomes derived from 300 samples aiming to forecast an atypical intervention count at the 2nd hour. Notably, a significant enhancement of 9.84% in RMSE is observed by leveraging a singular river height variable at the final hour within this timeframe, in contrast to the inclusion of alternative variables in prior horizons. Figures 4(a) and 4(b) visually depict the precision of predictions, exhibiting a maximum deviation of 0 to 17 errors for the 2nd hour before and after integrating the river height variable, respectively. Given that the XGBoost model generates decimal predictions (e.g.,

Table 4: Exploring the impact of Feature Selection on height of rivers analysis

Time horizon	Height of rivers	Feature Selection Technique	Rank
1h	La_Savoureuse_de_Belfort	Variance and XGBoost	38
2h	Le_Dessoubre	Variance, XGBoost and LightGBM	90
4h	Le_Drugeon	Variance and LightGBM	120
5h	Le_Doubs_de_Mouthe	Variance and LightGBM	51
9h	Le_Dessoubre	Variance, XGBoost and LightGBM	75
10h		Variance, XGBoost and LightGBM	65
11h	Le_Doubs_de_Labergement	Variance, XGBoost and LightGBM	45
14h	La_Savoureuse_de_Belfort	Variance and XGBoost	134
15h		Variance and XGBoost	78
17h	Le_Bourbeuse	Variance and LightGBM	111
19h	La_Rosemontoise	Variance, XGBoost and LightGBM	84
20h		Variance, XGBoost and LightGBM	53
21h	L'Allan	Variance and LightGBM	96
22h	La_Savoureuse_de_Giromagny	Variance and XGBoost	109
23h	La_Bourbeuse	Variance and LightGBM	122
	Le_Dessoubre	Variance, XGBoost and LightGBM	67
24h	Le_Doubs_canal_de_Besançon	Variance, XGBoost and LightGBM	31

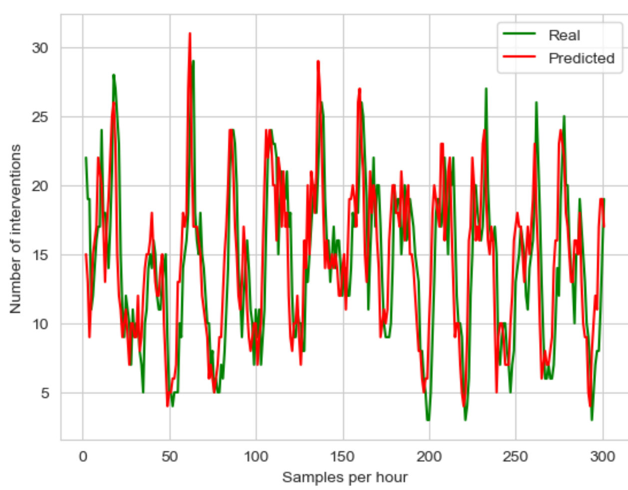
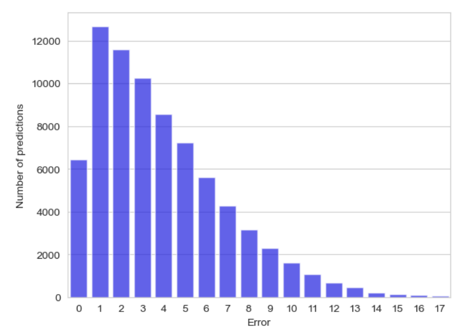
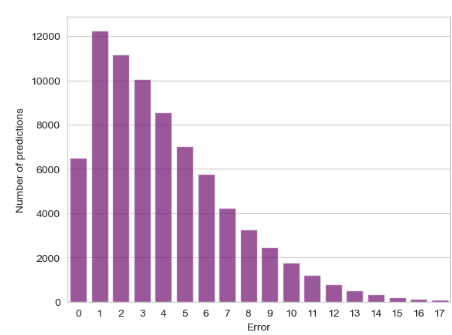


Figure 3: Prediction for the 2nd hour



(a) Prediction's error at the 2nd hour pre-selection



(b) Prediction's error at the 2nd hour post-selection

Figure 4: Insights from predictive modeling

8.32 interventions), the outcomes have been rounded to the nearest integer (here, 8 interventions) to align with practical applicability.

Significantly, XGBoost exhibited its most commendable RMSE score of 1.6500 at the 2nd hour, prominently influenced by the inclusion of one of the scrutinized river height variables, particularly that of the "Dessoubre" river. Noteworthy is the consistent enhancement in scores across temporal horizons owing to the recurrent selection of this variable, with certain rivers persistently contributing to score improvement for at least 2 hours, exemplified by the "Dessoubre," "Savoureuse," and "Rosemontoise" rivers at the 9th, 14th, and 19th hours, respectively. Subsequently, the XGBoost model underwent comprehensive training across all horizons via a meticulous grid search procedure for parameter tuning. This approach systematically explores diverse attribute combinations to ascertain the optimal solution. Table 6 and Table 7 furnish comprehensive insights into the identified and employed hyperparameters respectively for the best RMSE score at the second hour and the

Table 5: Insights into classification outcomes

Time horizon	Height of rivers	RMSE pre-sel	RMSE post-sel	Improvement
1h	La_Savoureuse_de_Belfort	2.9066	2.8898	0.58%
2h	Le_Dessoubre	1.6883	**1.6500**	2.32%
4h	Le_Drugeon	2.3412	2.3263	0.64%
5h	Le_Doubs_de_Mouthe	3.7112	3.6889	0.60%
9h	Le_Dessoubre	3.8322	3.8299	0.06%
10h		2.4238	2.3996	1.01%
11h	Le_Doubs_de_Labergement	3.5223	3.5022	0.57%
14h	La_Savoureuse_de_Belfort	2.3098	2.3054	0.19%
15h		3.4083	3.4038	0.13%
17h	Le_Bourbeuse	3.7851	3.7614	0.63%
19h	La_Rosemontoise	3.9134	3.8838	0.76%
20h		2.4863	2.4549	1.28 %
21h	L'Allan	3.5325	3.5309	0.04%
22h	La_Savoureuse_de_Giromagny	2.7966	2.6840	4.20 %
23h	La_Bourbeuse	3.7371	3.7186	0.50%
	Le_Dessoubre	3.9556	3.9335	0.56%
24h	Le_Doubs_canal_de_Besançon	2.8899	2.6307	**9.84%**

Table 6: Best hyperparameter for the 2nd hour

Hyperparameter	Values
max_depth	4
min_child_weight	4
gamma	0.2
subsample	0.9
colsample_bytree	0.8
learning_rate	0.1

Table 7: Best hyperparameter for the 24th hour

Hyperparameter	Values
max_depth	6
min_child_weight	2
gamma	0
subsample	0.9
colsample_bytree	0.9
learning_rate	0.02

greatest improvement percentage at the last hour, ensuring that the model achieves its maximal performance.

4 DISCUSSION

The present study aimed to assess the impact of river water level rise on firefighter intervention forecasting over nine years, from 2015 to 2024. Our methodological approach was carefully designed, involving meticulous data preparation and in-depth analysis to inform our experimental decisions. This included feature selection through various statistical techniques and machine learning methods. XGBoost was selected as the predictive model due to its robustness in handling outlier values, a particularly advantageous quality for continuous river height variables (see Table 1). Our methodology involved the implementation of an iterative training pipeline, in which features that improved the RMSE score over a 24-hour horizon were systematically selected (see Figure 2). The results, presented in Table 5, highlight the importance of variables associated with river height, particularly from the outset and during prolonged perennial periods. Notably, at the 2nd hour, the presence of the "Dessoubre" river contributed to a promising RMSE score of 1.65, which was able to continue improving the score in extended horizons, sometimes taking up to 2 hours. Furthermore, at the final hour, the selection of the "Besancon" river resulted in the most substantial RMSE improvement at 9.84%.

This observation suggests a persistent and progressive impact of river water level variables across all periods, highlighting their increased utility for both short and long-term forecasts. Thus, our findings indicate that certain river-related variables exert a notable influence across all horizons, owing to various temporal, topographical, and atmospheric influences. Consequently, it can be inferred from these results that there may be other variables producing delayed effects or other factors on river behavior influencing firefighter interventions. Weather conditions such as humidity and precipitation vary seasonally, while human activities such as dam construction, river diversions, and irrigation can also influence the distribution of river heights. Moreover the existence of complex topography, such as steep valleys or mountainous regions, where interactions between watercourses can lead to significant local variations in river height, resulting in varied consequences at different times of the day. This may explain why the impact becomes apparent from the outset and persists for extended hours. All these factors lead us to conclude that the potential impact of rising water levels on the environment is not negligible, its effects can have dangerous consequences, systematically triggering firefighter intervention.

The inquiry aims to comprehend why there aren't enough selected variables belonging to the river height family that could enhance prediction. For instance, considering the improved prediction outcome of 1.65 after selecting the "Dessoubre" river height at the 2nd hour, it becomes evident that other features from the

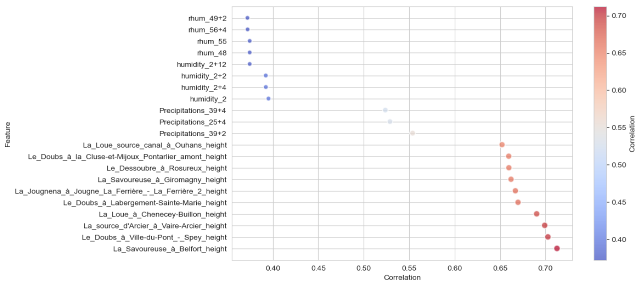


Figure 5: Correlation with the river "Le_Dessoubre" at the 2nd hour

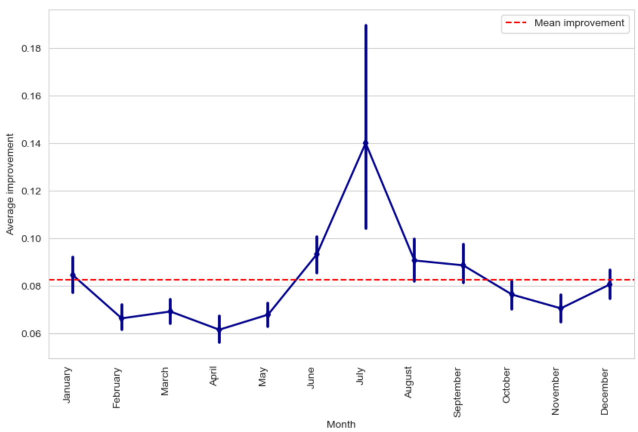


Figure 6: Improvement statistics per month

same category simply provide redundant information and cannot be chosen as they will not contribute to enhancing the prediction outcome. Moreover, as depicted in Figure 5, it becomes apparent, after calculating the correlation of variables in different categories with the river height feature, that variables belonging to the same family exhibit a high correlation, ranking them high, while also observing a correlation with other variables not belonging to the same family, such as precipitation and humidity, which is present in all horizons. The logical explanation for this result is an indirect causal correlation, implying that heavy precipitation could have an indirect influence on rising water levels. To delve deeper, a brief detailed analysis of the forecast improvement after selecting a variable belonging to the river height family, as shown in Figure 6, reveals a consistently higher average improvement in forecasts during the summer. This strongly advocates for the inclusion of variables from this family during this season to achieve promising prediction outcomes.

A detailed examination, as depicted in Figure 4, unveils a reduction in prediction errors, thus validating our findings. Specifically, the figure highlights a decrease in errors, notably an increase in 0 errors and a decrease in 1 and 2 errors, following the inclusion of the "Dessoubre" river height variable compared to errors observed before its inclusion. This study deepens our understanding of how river height influences firefighter interventions, presenting novel insights. However, certain limitations, such as the implementation of other boosting models or machine learning methods for comparison purposes, as well as the exclusive use of grid search for hyperparameter optimization, have tempered our results. Future avenues will involve exploring additional variables on other rivers, studying the combined impact of river height and meteorology, employing alternative models, and adopting more sophisticated sequential optimization approaches, such as Bayesian optimization.

5 CONCLUSION

This study represents a deeper dive within a series of articles aimed at investigating various categories of variables and their implications for firefighting interventions. Focusing on forecasting the number of future interventions, a critical aspect for firefighting services globally, this article explores the influence of river heights on emergency service predictions. Utilizing an extensive nine-year dataset from the Fire and Rescue Service (SDIS 25) in the Doubs region, France, the research examines how the predictive model strives to identify significant trends associated with river water level variables during distinct periods of the day. The findings suggest that variables in this category may have a sustained impact from the outset for an extended duration. For instance, the influence of the "Dessoubre" river from the 2nd hour until the 23rd hour underscores the increased utility of forecasts for prolonged time intervals. While this approach proves valuable for resource management and optimizing response times, ongoing enhancements are imperative for seamless integration into firefighting decision-making processes.

Continuing our research efforts, we will investigate the nuanced impact of variable categories (epidemiology, alert bulletins, events, etc.) on forecasts across various time horizons. We aim to extract valuable insights from these domains and identify the most influential variables based on intervention types and forecasting timeframes. By leveraging this information, we intend to refine our predictions, especially for short-term and long-term scenarios, by selecting models and their hyperparameters that align with the increased relevance of specific variables. Additionally, we will focus on integrating geolocated variables to fine-tune forecasts based on factors such as population density, forest area, etc. Our primary goal is to enhance our predictive capabilities, enabling the implementation of operational strategies that proactively address the demand for firefighting services.

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