**Abstract**

From early times, humanity has expressed a profound need to predict the future. In ancient Greece, oracles held a place of high respect, and influence. In modern times, the quest for accurate forecasting, has shifted to the realms, of research and science∙ empowered by advanced computational tools, provided by Artificial Intelligence, particularly Machine Learning. One of the fields, where Machine Learning, has established a fertile ground is in the domain, of forest fire management.

Forest fires, pose a major threat to both human, and animal life, with significant economic and social impacts. A reliable prediction system is crucial for mitigating these effects, especially during summer months, dry seasons, and in high-risk areas, such as the Mediterranean.

This study, explores feature construction, and selection methods, applied to forest fire data, collected over 10 years in Greece, incorporating prevailing weather conditions at ignition, and during suppression. By applying techniques like Principal Component Analysis (PCA), Minimum Redundancy Maximum Relevance (MRMR) feature selection, and Grammatical Evolution for feature construction, this research aims to identify key factors influencing fire duration.

These techniques, have become invaluable allies, in addressing complex predictive challenges, and advancing, our understanding of future events.

Our approach, leverages advanced computational methods, to analyze complex datasets, providing a deeper understanding of the primary drivers, of wildfire behavior, and enabling more effective mitigation strategies.

**Introduction**

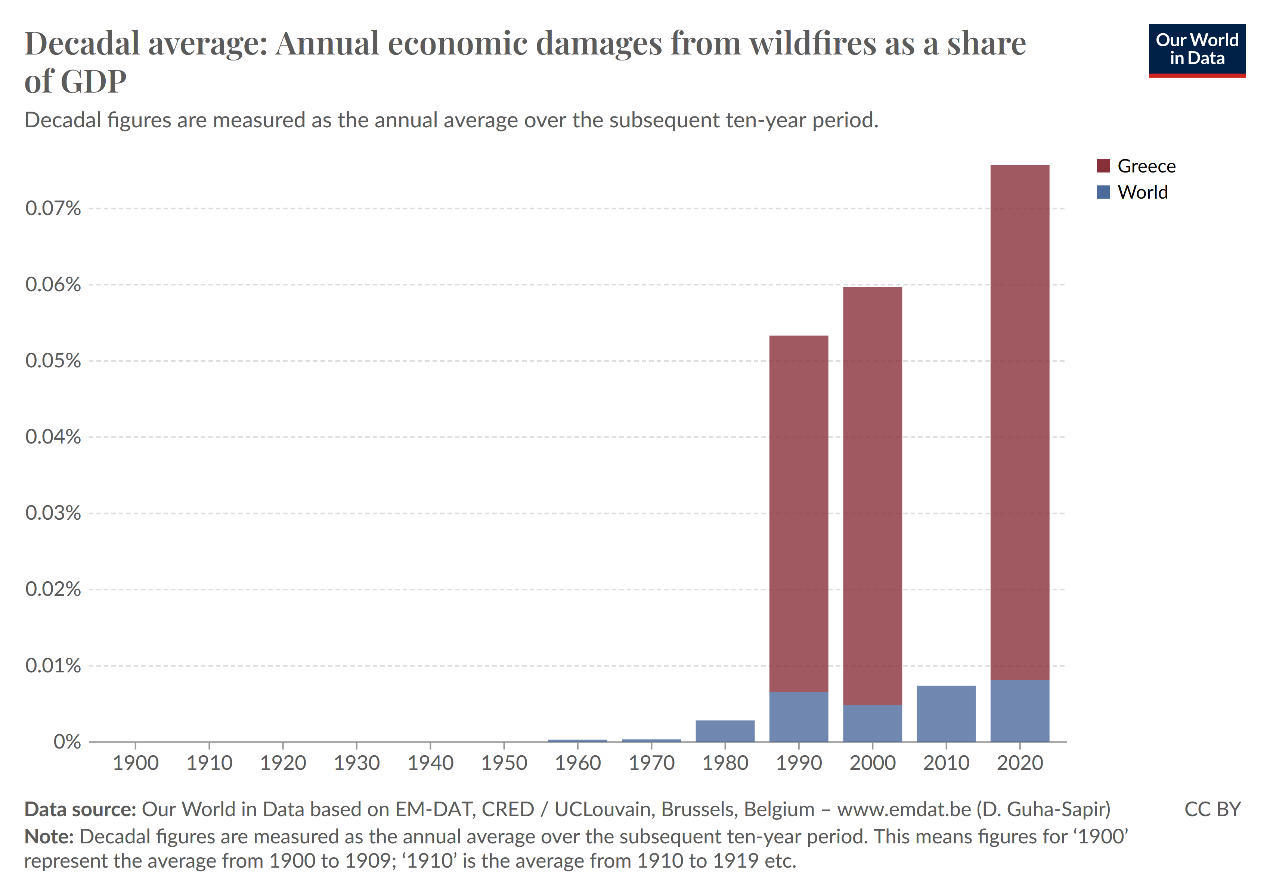
Fire, has always had a dual nature, in human history. On one hand, it has had the power to destroy civilizations, while on the other, it has significantly contributed to the evolution, of human society. From its destructive potential in warfare, and natural disasters, to its transformative role in technological, and cultural advancement, fire has shaped both, the rise, and fall of human civilizations. The ability to harness fire for cooking, metallurgy, and warmth played a crucial role in the development, of early human societies [[1](#_References._1)] ∙ while. its unchecked force, has also led to widespread devastation. This duality, underscores fire’s paradoxical role, in human progress: a force capable of both creation and destruction.

This notion, is also evident in ancient Greek mythology, particularly in the tale of Prometheus, who defied the gods by stealing fire, and gifting it to humanity. This act symbolizes the transfer of divine knowledge and power to humans, enabling progress and civilization. The myth, underscores fire's dual role, as a tool for human advancement, and as a source of conflict, illustrating the tension between progress and its ethical implications, as well as the costs of rebellion and innovation [[2](#_References._1)].

On this matter, fire, has played a multifaceted role in human history, both through myths and through its tangible impacts.

Nevertheless, in the modern era, wildfires are ranked among the most significant natural hazards [[3](#_References._1)], with immense effects on Earth's ecosystems, and human societies. Beyond that, according, the Chair, of ISO/TC 92, fire safety, Mr. P. Van Hees: ‘*With losses caused by fire estimated at 1% of the global GDP each year, fire safety must be viewed in the broader perspective of risk management and disaster mitigation’* [[4](#_References._1)].

In [Figure 1](#_Figures), it is illustrated, through a graphical representation, the economic burden, from forest fires, on the annual GDP.



**Figure 1***.* The economic impact of forest fires in Greece, and around the world.

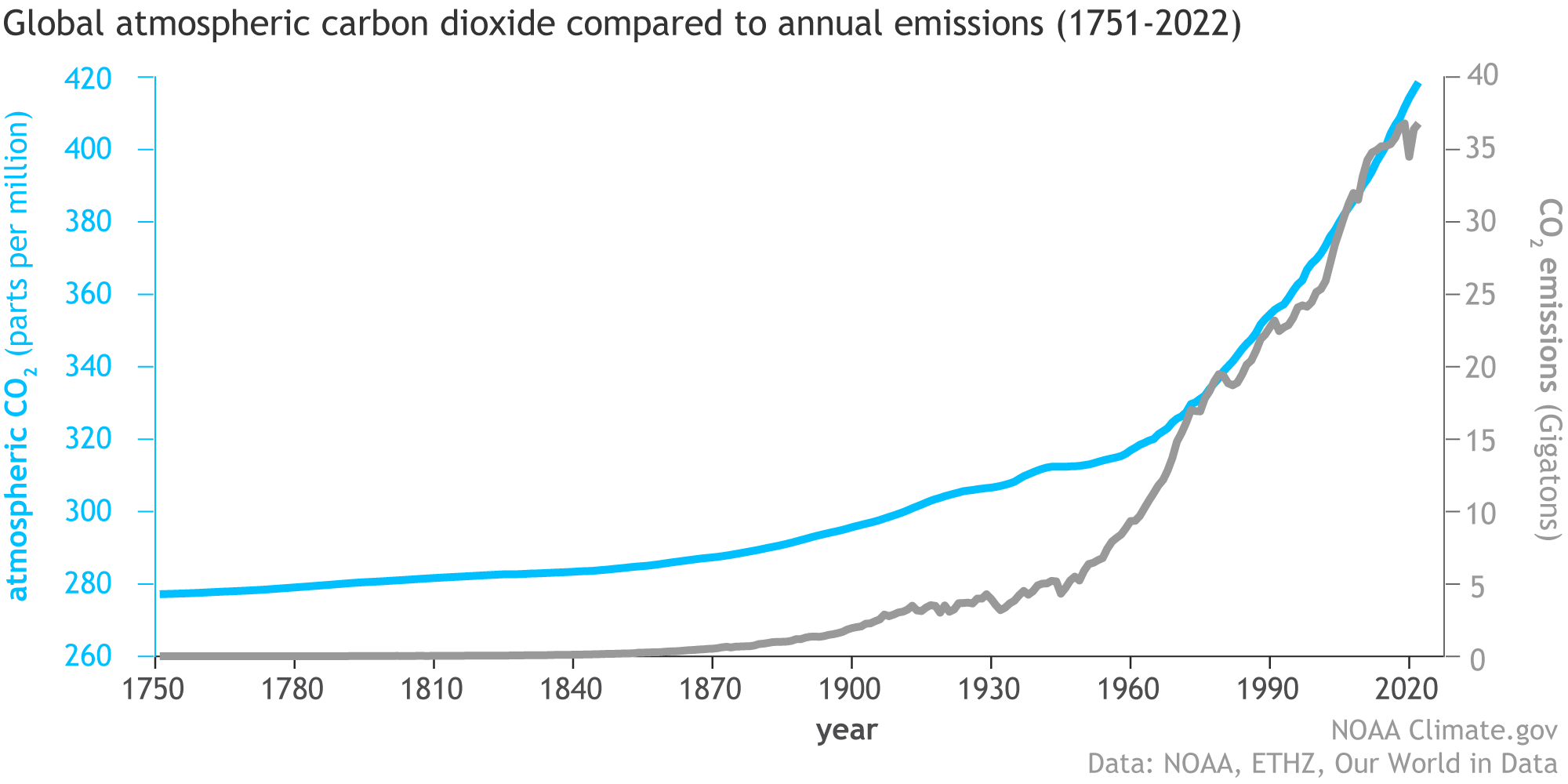
Namely:

* The cost of fire is estimated at about 1% to 2% of the annual GDP
* About 1% of fires are responsible for more than 50% of the costs
* The number of people dying in fire is estimated at 2.2 deaths per 100,000 inhabitants (based on 35 countries) [[4](#_References._1)].

In other words, wildfires and climate change, intensify each other. Climate change, exacerbates wildfires by increasing drought, high temperatures, low humidity, lightning, and strong winds, leading to more severe, and prolonged fire seasons. Conversely, wildfires contribute to worsening climate change [[5](#_References._1)].

Thus, wildfires (along with the extraction and burning of fossil fuels, and volcanic eruptions) exacerbate Climate Change, by further releasing carbon dioxide, into the atmosphere [[6](#_References._1)]. Also, the Mediterranean region is recognized as a key "hot-spot" for the impacts of climate change [[7](#_References._1)] At the same time, the critical need to address climate changes, effects on wildfire patterns, is highlighted, as essential for protecting both the environment, and public health in Greece [[8](#_References._1)].

In [Figure 2](#_Figures), we observe the continuous increase in carbon dioxide levels, beginning in 1751.



**Figure 2.** The environmental impact of carbon dioxide.

Concerning this, the United Nations of Environment Programme, are calling the governments: “*to radically shift their investments in wildfires to focus on prevention and preparedness*” [[5](#_References._1)].

Therefore, despite the challenging circumstances posed by Climate Change, driven by continuous human expansion, and technological progress, we aim to transform this disadvantage into an advantage, by focusing our efforts on advancing technology itself. On this, Artificial intelligence, particularly Machine learning, emerges as a valuable ally in addressing this global issue, offering innovative solutions and supporting sustainable development [[27](#_References._1) ,[9](#_References._1)].

Machine learning, refers to a collection of techniques, and algorithms, that enable systems to identify patterns, and make decisions based on data, improving their performance over time, without explicitly being programmed for specific tasks [[10](#_References._1)].

This was the vision, of Alan Turing, when, in 1936, he wrote his PhD ‘*On Computable Numbers, with an application to the Entscheidungproblem*’ [[11](#_References._1)].

Namely, Machine learning, is a pivotal branch of artificial intelligence, presents endless opportunities for businesses, and society alike. Beyond its numerous advantages, it plays a critical role in driving groundbreaking advancements, in Climate Change adaptation, and mitigation. By accelerating, the development of solutions, to some of the most pressing challenges facing the planet∙ machine learning, is reshaping the way we address global environmental issues [[10](#_References._1)].

Although, modeling complex environmental variables, often presents challenges, due to the significant computational resources required, and the diversity or complexity of data formats [[12](#_References._1)].

Machine learning algorithms, however, can bypass these challenges, by deriving mappings, and relationships directly from the data, eliminating the need for predefined expert rules. This capability, is particularly beneficial when dealing with scenarios, involving a large number of parameters, with intricate physical properties, such as in forest fires. Consequently, adopting a machine learning approach to fire management, can help overcome many of the limitations, associated with traditional physics-based simulation models [[12](#_References._1)].

Regarding this, in the global literature, significant interest has been developed, in the role of machine learning, in the field of fire management [13]. Forest fires, however, have not been extensively studied, as research on forest fires constitutes only 2.9% of the global literature, according to a study conducted between 2017 and 2021 [[50](#_50)_Drakaki,_M.,)]. More specifically, floods have received the most attention in research (20.3%), followed by earthquakes and hurricanes, each accounting for 18.8%. Studies on general disaster types make up 15.9%, while landslides account for 10.1% [[50](#_50)_Drakaki,_M.,)]. Notably, depending on the area of focus, researchers employ corresponding algorithms, to address specific challenges.

In the following (Figure 3), we observe the machine learning algorithms, utilized according to the domain problem. Specifically, there are three main types, of machine learning, as we can see in [Figure 3.](#_Figures)



**Figure 3.** Machine Learning Types.

In this respect, the science of forest fire management: is a distinct field encompassing six key problem domains. [[14](#_References._1)].

These, domains include: fire detection, fuel characterization and mapping **/** climate change and fire weather **/** fire susceptibility, occurrence and risk **/** fire behavior prediction, fire effects **/** and fire management [[12](#_References._1)].

At this point, we will examine studies, in summary, conducted using algorithms, in the field of forest fires.

**Bayesian networks**, have been widely utilized in the context of forest fires, particularly for predicting, and analyzing, potential causes of fires [[52](#_References._1)]. Additionally, a recent study employed Bayesian networks to model the cascading effects of drought and forest fires [[53](#_References._1)]. Also, Bayesian networks were integrated, with deep learning techniques, to detect fires, from video frames [[54](#_References._1)].

**Naïve Bayes**, has been applied to forest fire-related challenges, in numerous studies. For instance, Nugroho, developed a forest fire prevention system, that combines a wireless sensor network, with a Naïve Bayes classifier [[55](#_References._1)]. Zainul's work proposes a method for classifying hotspots responsible for forest fires using the naïve Bayes algorithm [[56](#_References._1)]. Karo, proposed a methodology for wildfire classification, that incorporates feature selection, and employs Naïve Bayes, alongside other machine learning techniques [[57](#_References._1)].

**Logistic Regression**, has been applied to various forest fire-related issues, including estimating human-caused wildfire risk [[58],](#_References._1) predicting wildfire vulnerability [[59](#_References._1)], probabilistic modeling of wildfire occurrence [[60](#_References._1)], and analyzing wildfire danger [[61](#_References._1)].

**(OK)**Several studies, have utilized **Αrtificial Νeural Νetworks (ANNs),** in the field of forest fire prediction, and monitoring. For instance, Hossain, employed ANNs to detect flames and smoke based on static image features [[62](#_References._1)]. Lall and Mathibela applied neural networks to predict wildfire risk in Cape Town [[63](#_References._1)]. Similarly, Sayad, utilized neural networks, along with other machine learning techniques, for wildfire predictive modeling, using data from NASA’s Land Processes Distributed Active Archive Center (LP DAAC) [[64](#_References._1)]. Additionally, Gao, recently published a case study, on predicting wildfires, in a Chinese province, using neural networks [[65](#_References._1)].

The **J48** algorithm, alongside other machine learning models, was employed, to predict forest fires [[66](#_References._1)].

**Random Forest**, has been widely utilized, in forest fire prediction. For instance, Latifah, applied Random Forest, to predict forest fires, in Borneo [[67](#_References._1)]. Similarly, Malik, proposed using Random Forest, to estimate, wildfire risk in Northern California [[68](#_References._1)]. Additionally, Gao, conducted a forest fire, risk prediction study in China, combining Random Forest, with a neural network trained, using the back-propagation method [[69](#_References._1)].

Nevertheless, the domain explored in this research is unprecedented, as previous studies, have primarily focused on different aspects. On this matter, we will reference in very few studies, that have approached the topic of estimating the duration, of a fire.

* Xiao, developed a wildfire duration prediction model, based on historical fire data, and geospatial information. The algorithms, employed included: RF (Random Forest), KNN, and XGBoost regression models, as well as image-based approaches such as CNN and Encoder. The model, achieved an accuracy exceeding 80%, for fires lasting longer than 10 days. Beyond this, however, the model did not achieve a satisfactory R² score [[13](#_References._1)].
* Andela, validated the fire data from the Global Fire Atlas, using independent datasets, from the United States. The study utilized satellite data, and highlighted, that the duration of fires is significantly influenced, among others by the fire season [[15](#_References._1)]
* Ujjwal, settled a surrogate model, to capture the dynamic spread, of a wildfire over time. The surrogate model, designed to simulate the relationship between the burned area and key meteorological parameters (such as relative humidity, temperature, and wind speed), provides valuable insights, into fire behavior across different [[16](#_References._1)]. Although, the research did not explicitly focus on predicting the duration of a fire, its findings could be utilized to estimate fire duration indirectly.
* Wang, also conducted research that, while capable of yielding results for predicting, wildfire duration∙ primarily, focused on forecasting the scale of a forest fire. The study utilized neural network algorithms, including Backpropagation Neural Network (BPNN), Recurrent Neural Network (RNN), and Long Short-Term Memory (LSTM). Among these classification methods, LSTM demonstrated the highest accuracy, achieving 90.9% [[17](#_References._1)]
* Kopitsa et al., focused on predicting fire duration, in Greece, using machine learning techniques. Specifically, it compared the performance of various algorithms, including: Bayes Net, Naive Bayes, Logistic Regression, Multilayer Perceptron (MLP), J48, and Random Forest. Among these, Random Forest demonstrated the highest accuracy, achieving 87–92% in predicting forest fire duration [[14](#_References._1)].
* Xi, settled a framework, for jointly, modeling fire duration, and size using a bivariate finite mixture model. Four subpopulations (normal or extreme in duration and size) were analyzed, incorporating, variables such as: location, month, and environmental factors. The analysis, revealed a strong correlation between: duration, and size, and identified key predictors, influencing these subpopulations [[18](#_References._1)].

Predicting, the duration of a fire is crucial, as it allows for estimating the potential damage, to the affected area and determining the necessary human resources, for its suppression [[14](#_References._1)]. Besides that, forest fires and climate change are commonly exacerbating [[5](#_References._1)].

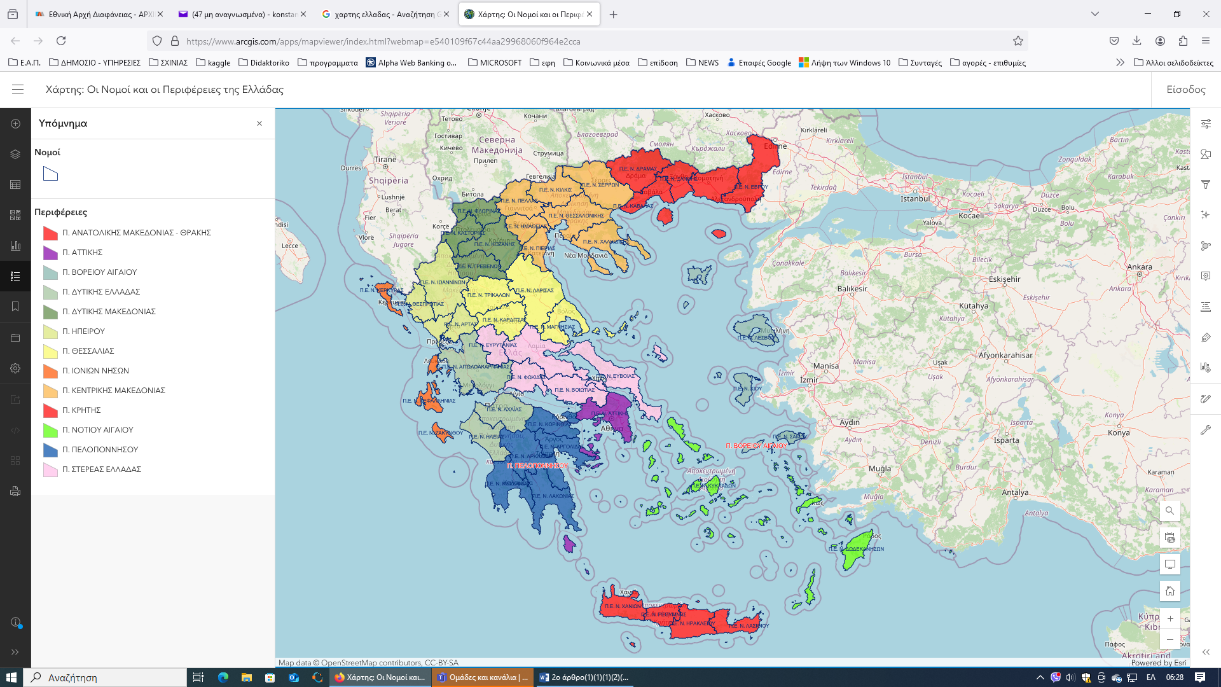
The Western fire chief’s association, from the U.S. emphasizes that climate change is drastically impacting the fire season. As a result, fire seasons now last six to eight months, compared to the four months, they previously spanned [19]. Face the Facts USA reports that, in the U.S., the average duration of wildfires increased from 8 days, before 1986, to 37 days by 2013 [[19](#_References._1)].

Consequently, the noteworthy contribution, of our study lies in its focus on predicting the duration of a forest fire, in Greece∙ and more specifically, in identifying the feature characteristic, that significantly influences its duration.

**Study Area**

**Figure 4. Map of Greece**

The country, of interest, in our research is Greece, located in the Mediterranean region of Europe. According to the European census conducted by the Hellenic Statistical Authority in 2021, Greece has a permanent population of 10,482,487. The total area of the country is 131,957 square kilometers. The forests, and woodlands, cover the 49.5%, of the total land [[51](#_51)_Xepapadeas,_A.,)].



The Mediterranean climate, is characterized by mild winters, and hot, dry summers. Precipitation, is relatively infrequent, occurring primarily during the wet seasons, of autumn, and winter. However, extreme weather events, such as sudden and intense rainfall or thunderstorms, are not uncommon [[20](#_References._1)].

It is evident that Greece, like other Mediterranean countries, faces a challenging combination of climatic conditions, that increasingly contribute to more severe, and frequent, forest fires. These fires have significant repercussions for the natural environment, cultural heritage sites located in or near forested areas, agriculture, livestock, and rural life as a whole [[21](#_References._1)].

Wildfires, in the Mediterranean region, have become increasingly severe, and hazardous, with scientists identifying the emergence of a "sixth-generation megafire" directly linked to global changes [[14](#_References._1)]. This new type of wildfire first occurred in Portugal and Spain in 2017, resulting in over 120 fatalities, and later in Greece in 2018, where it claimed 104 lives. According to the 2019 WWF report, these fires are characterized by their extreme intensity, uncontrollability, and high lethality available from <http://awsassets.panda.org/downloads/wwf__the_mediterranean_burns_2019_eng_final.pdf>

In Greece, over 5,000 wildfires occur annually, according to data obtained from the Hellenic Fire Service.

**Materials and Methods**

This section presents the datasets that are used in the experiments, as well as the machine learning techniques that are applied to these datasets.

**The Used Datasets.**

In this paper, publicly available data provided by the Hellenic Fire Service, were utilized, at the link: <https://www.fireservice.gr/el_GR/synola-dedomenon> (accessed on December 6, 2024).

The dataset, covering the years 2014–2021, underwent preprocessing before being used in machine learning models. It aligns with the objectives of the European transparency legislation 2013/37/EU, ensuring it is free from bias related to type or location and encompasses all fire incidents across Greece. The data provided by the Hellenic Fire Service is readily accessible, regularly updated, reliable, inclusive of all involved parties, and facilitates comprehensive analysis.

The initial 57.989 datasets, comprised both numerical, and alphanumeric data∙ including details about the location, of the forest fire, and information regarding the fire station involved, in the suppression efforts.

Beyond these data, our research was enhanced by incorporating meteorological information, for each fire incident. Specifically, we included weather conditions, at the time the fire began, and at the time it was extinguished. As a result, we incorporated an additional 115,978 data points encompassing various climatological factors, such as: wind speed, humidity, temperature, sunrise and sunset times, among others. The meteorological data, are available from: <https://opencagedata.com/about> (accessed on December 6, 2024).

The initial step, in Hellenic Fire data preprocessing, involved digitizing columns, containing alphanumeric data, particularly those with numerical content. This process entailed, converting categorical values into discrete integers, to ensure compatibility with machine learning algorithms, which require numerical inputs. Subsequently, a critical step was addressing missing values. Records with missing entries in key features, such as climatic variables or other relevant data, were excluded from the dataset. These omissions typically occurred due to unavailability, at the time of recording, and could potentially result in biased or unreliable outcomes.

To define the output variable, the duration of each forest fire was converted from hours or other time units into minutes, ensuring greater precision in classification. A logarithmic transformation of fire duration in minutes was then applied to manage the wide range of values effectively, preventing excessive influence from extreme durations. Based on this transformation, three distinct categories were established, serving as target values for experimental analysis. This approach enabled the classification of forest fires according to their duration. For the Greek forest fire data used in this study, the following classification scheme was adopted:

1. Up to 360 minutes (6 hours) is considered to be a fire, of short duration.
2. From 361 – 7200 minutes (6 hours – 5 days) is a fire of medium duration.
3. From 7201 - …. for the duration it persists (5 days - and more) is considered a long duration.

**Feature Construction**

To improve the predictive accuracy of Machine Learning (ML) models in forest fire analysis, there is increasing emphasis on leveraging **Feature Construction techniques**. These methods involve creating new, meaningful variables by combining or transforming existing data attributes [[22](#_References._1)]. For example, integrating material resources deployed during a forest fire event into a single metric constitutes feature construction, enabling models, to better capture the complexity, of fire incidents, and resource allocation. Another example, for Feature Construction, during a forest fire, is combining weather attributes, in order to form, a fire risk index. Such, approaches enhance data representation, facilitating more robust, and interpretable predictive models, in disaster management.

Τhis paper provides a concise overview of Feature Construction methods, applied to predicting forest fires, and improving early detection, systems. It also offers a comprehensive review of current models used in this field, highlighting their strengths and limitations.

In the domain of fire management, early warning systems for fire outbreaks serve as the cornerstone for timely containment and mitigation efforts. Over recent years, extensive research has been conducted to enhance fire detection methodologies through advanced computational techniques.

For instance, Harkat, utilized **feature construction** to train a model on multidimensional data. By eliminating irrelevant or redundant features and selecting the most relevant ones for classification, their approach achieved a remarkable accuracy of **96.21%.** However, their study also revealed limitations in the performance of deep learning (DL) models under constrained conditions [[23](#_References._1)].

Another significant contribution is the work by Zhang, which demonstrated that every feature is integral to the overall performance of their algorithm. The combined use of features resulted in a highly impressive accuracy rate of **99.02%** for forest fire recognition. Nevertheless, the study identified a critical weakness: the removal of a single feature (mean) led to a substantial increase in false positives, underscoring its importance in minimizing errors [[24](#_References._1)]

Similarly, Yang, explored the construction of novel, dynamic features to improve accuracy and reduce false alarms in fire detection systems. By combining smoke and flame characteristics, their approach focused on enhancing early warning capabilities. However, the study had notable limitations, as it failed to disclose the source of their data or the specific results obtained, thereby impacting its reproducibility and transparency [[25](#_References._1)].

At this point, we will mention a novel method, that was introduced by Tsoulos, for Featured Constructions. In order to improve the effectiveness of Artificial Intelligence, tools, such as Radial basis function (RBF), Multi-layer perceptron (MLP), K-nearest neighbor (KNN), and Neural Networks. The proposed method, is an experimental comparison, carried out against the accuracy obtained, on the original features, as well on features created by the PCA method, [[26].](#_References._1)

**Principal Component Analysis (PCA)**

The **Principal Component Analysis** (PCA) technique, introduced by mathematician Karl Pearson in 1901, and developed by Harold Hotelling (1933). This technique, operates on the principle when data from a higher-dimensional space is transformed into a lower-dimensional space, the resulting lower-dimensional representation should retain the maximum variance, of the original data.

Notably, it is worth mentioning that the use of PCA, on larger datasets, became practical only after the advent of electronic computers, which made it computationally feasible, to handle datasets, beyond trivial sizes [(28).](#_References._1)

Continuing, with the applications of PCA, it is a widely utilized technique in exploratory data analysis, and machine learning∙ particularly, in building predictive models. It is an unsupervised learning method, designed to analyze, the relationships among a set of variables. Often referred to as a form of general factor analysis, it involves regression to determine a line of best fit. The primary objective, of PCA, is to reduce the dimensionality of a dataset, while retaining the most significant patterns, and relationships, among the variables, all without requiring prior knowledge, of the target variables [(29).](#_References._1)

Next, we will briefly reference studies, that have utilized PCA, covering different areas, such as: statistical physics, genetic improvement, face recognition, economic & environmental sciences, medical prediction, e.t.c.

Explicitly, the research conducted, by Park (2024), highlights the reasons behind the success of the PCA technique, for lattice systems. The study's primary limitation lies in the dependency of the proposed formula's accuracy on the dataset size. Specifically, the results achieve full precision, only under the condition of an infinite dataset. This constraint restricts the practical applicability, of the method, when working with finite or limited data, a common scenario, in real-world analyses, [[30].](#_References._1)

The following research, by Sarma, (2024), performed with PCA, in order to evaluate, morphometric traits, under a multivariate approach. The findings suggest, that PCA could significantly enhance the genetic improvement, [[31].](#_References._1) Noteworthy, is the fact, that the 64.29%, of the total variance explained, can be considered relatively low. This suggests, that a significant amount of unexplained information remains, which is not captured, by the four principal components.

The next study, by Parante, the PCA was used for monitoring the cultivation, of cannabis, in Albania. Specifically, with PCA they remove redundant spectral information from multiband datasets, [[32].](#_References._1)

The article, by Slavkovic & Jevtic, presents the implementation of a face recognition system based on the Principal Component Analysis (PCA) algorithm [[33](#_References._1)].

The PCA technique was utilized, by Hargreaves, for stock selection, specifically to identify, a limited number of stock variables, that could effectively aid, in determining winning stocks, [[34].](#_References._1)

The following documents present a modified model of Principal Component Analysis (PCA).

The paper, by Xu (2024), presents an interesting example of a modified application of Principal Component Analysis (PCA)∙ utilizing, both linear and non-linear methods, through Kernel PCA (KPCA), in combination, with the Adaptive Boosting (AdaBoost) algorithm, [[35].](#_References._1)

The study, by Zhang (2022), a neural network model, combining PCA and Levenberg-Marquardt Backpropagation (LMBP) was developed, to efficiently, and accurately analyze, and predict the interaction between IAQ and its influencing factors. In particular, it was examined indoor air quality (IAQ), and its relationship, with building features, and environmental conditions, [[36].](#_References._1)

In the next research, by Akinnuwesi, it was employed a hybrid approach, combining Principal Component Analysis (PCA), and Support Vector Machine (SVM). They create, the Breast Cancer Risk Assessment and Early Diagnosis (BC-RAED) model, designed to accurately detect BCa, in its early stages. PCA, was initially applied to extract features, during the first preprocessing stage, followed by further feature reduction, in the second stage. The multi-preprocessed data, were analyzed for breast cancer risk, and diagnosis using SVM. The BC-RAED model, achieved, an accuracy of 97.62%, a sensitivity of 95.24%, and a specificity of 100% in assessing, and diagnosing breast cancer risk, [[37].](#_References._1)

Subsequently, we will briefly mention certain studies, that have been conducted, in the field: of Forest Fires.

Guan's, research focuses on forest fire prediction using PCA-preprocessed data. The preprocessing step removed irrelevant information, simplifying analysis. Linear regression and random forest methods were then applied, revealing temperature, relative humidity, wind, and rain as the most influential factors in forest fire occurrence, [[38].](#_References._1)

A novel model was developed, by Nikolov, using meteorological forecast data as input. Principal Component Analysis (PCA), with orthogonal rotation, was applied to reduce 195 meteorological variables, from the NARR dataset, to a smaller set of significant fire-ignition predictors, later used in logistic regression, to calculate wildfire ignition probabilities, [[39]](#_References._1) .

Like the aforementioned study, this one also belongs to Nikolov. This research, focuses on predicting wildfire ignitions, caused by lightning strikes, which account for the largest area burned annually, in the extratropical Northern Hemisphere. Principal Component Analysis (PCA), played a key role, in reducing 611 potential predictors, to 13 principal components, which were used in logistic regression to identify the primary factors influencing lightning occurrence, [[40].](#_References._1)

**Minimum Redundancy Maximum Relevance (MRMR)**

The min-redundancy max-relevance algorithm, introduced by Chris Ding and Hanchuan Peng, in their 2005 paper titled: “Minimum Redundancy Feature Selection from Microarray Gene Expression Data.” The (MRMR) aims to optimize feature selection, by minimizing redundancy, and maximizing relevance by Ramirez – Gallego [[41](#_References._1)].

In sum, MRMR enhances relevance-only methods, such as using an f-test between the target, and the features. When two features are similar, MRMR prioritizes only the one, with the highest relevance.

From the literature review conducted, no studies, were identified, that specifically utilized the m RMR algorithm, in the domain, of forest fire research. Therefore, we will proceed, to reference other relevant studies, from other fields.

The study, by Zhao, extends traditional m RMR methods, by introducing, a **non-linear feature redundancy measure,** anda **model-based feature relevance measure**∙which are tested, on synthetic, and real-world datasets. Based on its empirical success, m RMR is integrated, into Uber's marketing machine learning platform, to automate, the creation and deployment, of scalable targeting, and personalization models, [[42].](#_References._1)

In the next paper, by Yang, the m RMR (Minimum Redundancy Maximum Relevance) algorithm is utilized in conjunction with a Random Forest (RF) model to perform **feature selection** in the context of air quality prediction. MRMR, is employed, to determine which variables have the most significant impact, on the air quality index (AQI), while minimizing redundancy among them, [[43].](#_References._1)

The article, by Elbeltagi, is an innovative approach, for estimating maize chlorophyll, by integrating hyperspectral indices with cutting-edge, six advanced machine learning techniques. The MRMR algorithm was incorporated into the process to enhance feature selection by pinpointing the most significant spectral bands, minimizing data redundancy, and boosting model efficiency, [[44].](#_References._1)

In the energy sector, Liu conducted the following research, offering an improved method, for predicting transient stability, in power systems. The m RMR algorithm, is applied for feature selection, with minimal redundancy and maximum relevance, providing an enhanced approach, for forecasting transient stability, in power systems.

This approach addresses, the limitations of previous methods, such as low accuracy, difficult applicability, and high computational cost, while incorporating the "winner take all" (WTA) technique, for ensemble learning, and enhanced precision, [[45].](#_References._1)

Eristi, also refers to the energy sector. Specifically, this paper presents, a new PD detection system, that combines spectral analysis, spectrogram analysis, deep learning algorithms, minimum redundancy-maximum relevance (m RMR), and ensemble machine learning (EML). The most impactful features, are identified, by performing m RMR feature selection analysis, on the extracted deep features, [[46].](#_References._1)

Zhang, employed an Acoustic Emission (AE) technique to monitor, inaccessible areas of large storage tank floors, utilizing AE sensors positioned externally to the tank. The implemented algorithm, effectively distinguishes corrosion signals from interference signals, particularly drop-back signals induced by condensation. Experimental studies were conducted both in laboratory settings and in field environments, focusing on Q235 steel. Seven characteristic AE features, derived from signal hits, and frequency, were extracted, and subsequently selected for pattern recognition, using the Minimum Redundancy Maximum Relevance (m RMR) method, [[47]](#_References._1) .

Razmi, proposes a methodology to examine the effects of climate change, on sea level variations, in coastal areas, using an artificial neural network model. Feature selection techniques, including Minimum Redundancy Maximum Relevance (MRMR) and Mutual Information (MI), are employed to identify the most suitable predictors for the neural network input, [[48].](#_References._1)

The study, by Gui, introduced an innovative predictive screening approach, integrating mutual information (MI), and Random Forest (RF) methodologies, through the minimum-redundancy-maximum-relevance-recursive feature elimination-random forest (mRMR-RFE-RF) framework. This method, combines the strengths of both filter, and wrapper techniques, offering a comprehensive strategy for feature selection, [[49].](#_References._1)

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This was the vision, of Alan Turing, when, in 1936, he wrote his PhD ‘*On Computable Numbers, with an application to the Entscheidungproblem*’ [[11](#_References._1)].

Namely, Machine learning, is a pivotal branch of artificial intelligence, presents endless opportunities for businesses, and society alike. Beyond its numerous advantages, it plays a critical role in driving groundbreaking advancements, in Climate Change adaptation, and mitigation. By accelerating, the development of solutions, to some of the most pressing challenges facing the planet∙ machine learning, is reshaping the way we address global environmental issues [[10](#_References._1)].

Although, modeling complex environmental variables, often presents challenges, due to the significant computational resources required, and the diversity or complexity of data formats [[12](#_References._1)].  [C., Su, C.Y. *Wildfire Flame and Smoke Detection Using Static Image Features and Artificial Neural Network.* In Proceedings of the 2019 1st International Conference on Industrial Artificial Intelligence (IAI), Shenyang, China, 23–27, pp 1-6. July 2019.](#A67) **Available from:** <https://ieeexplore.ieee.org/abstract/document/8850811?casa_token=gzl-irpkh0sAAAAA:4bpZE96jGP2bLPXtheTwq5OGko4vpM-wX99v9Q6eEXXieVstTsfZOije4g2dqY600_KAgrCC0cs> (accessed on December 15, 2024).

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