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Cyprus tomorrow RECOVERY AND RESILIENCE PLAN

Republic of Cyprus

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Executive Summary

Wildfires represent a growing threat to ecosystems, infrastructure, and human life, a situation worsened by climate change and the expansion of human activity into fire-prone regions. This document presents the design and implementation of a data-driven Fire Detection, Prevention, and Response (FDPR) system, leveraging advanced analytics and intelligent algorithms to address this escalating challenge.

The FDPR system processes a wide array of sensing and imaging data—collectively known as fire indices—using a combination of rule-based logic and machine learning techniques to detect patterns and anomalies indicative of fire risk. These algorithms enable faster and more accurate decision-making, significantly reducing response times and enhancing fire mitigation efforts.

Central to the system is Work Package 3 (WP3), which provides essential sensing data and image processing inputs. This data supports both real-time monitoring and probabilistic fire risk categorization, based on key environmental and human-related factors such as land cover, topography, and proximity to infrastructure. The result is a five-level fire risk index, from very low to very high, used to assess regional fire probability and prioritize areas for attention.

This document details the framework, methodology, and operational vision of the FDPR system, laying the foundation for a scalable, intelligent, and proactive wildfire management solution.

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1. Introduction

Wildfires pose an increasingly severe threat to ecosystems, infrastructure, and human life, driven by climate change and expanding human settlements in vulnerable areas. To address this pressing challenge, this document outlines the development and implementation of advanced analytics algorithms for Fire Detection, Prevention, and Response (FDPR). These intelligent algorithms are designed to ingest and analyse a broad spectrum of sensing and imaging data, enabling a systematic, data-driven approach to wildfire detection and risk mitigation.

At the core of the fire module is the capability to process diverse data inputs—referred to as fire indices—and to identify patterns and anomalies through rule-based detection and machine learning techniques. By uncovering emerging trends in the data, the algorithms will support more informed decision-making and significantly reduce reaction times to potential fire threats. These technologies are being developed with a strong focus on real-world applicability, closely aligned with the requirements and data types defined in Work Package 3 (WP3).

WP3 serves as the foundational data source, providing critical sensing and image-processing inputs. This data will be used not only for real-time monitoring but also to categorize fire risk using probability-based models. The categorization will consider multiple environmental and anthropogenic parameters, including:

- Land Cover: Biophysical characteristics such as vegetation type and density
- Topography: Slope orientation (aspect) and elevation
- Human Factors: Proximity to residential areas and road networks

These factors will contribute to the formulation of a five-level fire risk index—ranging from very low to very high. The FDPR system will use this risk index to assess fire likelihood across different regions and identify probable fire locations. In the event of a fire detection, autonomous drones will be deployed for rapid, in-situ verification, serving as an early warning mechanism to support prevention efforts and reduce fire spread.

Additionally, the FDPR algorithms will enhance coordination between first responders and emergency services. By evaluating current response strategies and offering data-informed recommendations, the system aims to streamline interventions and improve outcomes. The user will interact with the FDPR system via a unified user interface (UI), developed as part of WP3 (Tasks 3.3 and 3.4), accessible through a standardized API designed for seamless integration and usability.

This document presents the framework, methodology, and envisioned implementation of the FDPR mechanism, setting the stage for a proactive and intelligent wildfire management solution.

2. Fire Prediction Module

2.1 Introduction

Accurate prediction of wildfire occurrence remains a complex and multifaceted challenge. The difficulty stems from the intricate interplay of environmental, meteorological, ecological, and human factors, all of which exhibit significant spatial and temporal variability. Wildfires are driven by a multitude of interdependent variables including vegetation type, fuel moisture, topography, and soil conditions. These factors interact in nonlinear ways, making it difficult to model fire risk accurately. Small changes in one parameter can have disproportionate effects, especially under extreme conditions. In addition, weather plays a critical role in fire ignition and propagation. Variables such as temperature, humidity, wind speed, and atmospheric stability are highly dynamic and can change rapidly. Despite advances in meteorological forecasting, uncertainties in short- and long-term weather predictions significantly affect the reliability of fire risk models.

In this section we present the research performed to develop a fire prediction module based on weather data combined with the available fire history from 2010 until 2018.

2.2 Current Fire Prediction Practices

Modelling fire processes across multiple scales requires expertise in wildfire science. The combination of an ignition source and adequate conditions for the fire to spread leads to the probability of a fire (Oliveira et al., 2012). The causes of forest fires are diverse, and their distribution varies from country to country and can also vary spatially and temporally within the same country (Ganteaume et al., 2013).

The causative factors of wildfires often fall into two main categories: environmental and anthropogenic (Bountzouklis et al., 2022) or into four subcategories: topography, climate, vegetation, and human activity (Jaafari & Pourghasemi, 2019). Many factors are thought to influence wildfire activity, including weather conditions such as wind speed/direction, air temperature, relative humidity, solar radiation and rainfall (Benson et al., 2008), human activities like grazing, resin collection etc. (Palaiologou et al., 2020), land use change like land abandonment or tourism infrastructures (Butsic et al., 2015; Rasilla et al., 2010; Rego, 1992), fuel properties and climate as higher temperatures will result into drought of vegetation which will be more flammable (Dimitrakopoulos et al., 2011; Jolly et al., 2015).

According to Bradstock and Boer et al. there are four major environmental factors which control the occurrence of large wildfires. These are (a) accumulation of fuel to levels that favor fire spread, (b) drying of the fuel to allow ignition and maintenance of combustion, (c) ignition sources (lightning, arson, etc.), (d) fire weather conditions that favor the spread of fire (Boer et al., 2017; Bradstock, 2010). Actually, in some ecosystems, we can have a significant impact on the frequency and degree of wildfires by fuel management with prescribed burning (Manjón-Cabeza et al., 2020; Morgan et al., 2020; Tambelini Tizianel et al., 2020), however this is not always a feasible or practical solution (Davim et al., 2021; Palaiologou et al., 2020).

In large terrains, especially in rugged terrains, there is often a lack of knowledge about the influence of the respective geological environment features, which can lead to reduced wildfire prediction accuracy. Therefore, determining the importance of geoecological factors is a recurring challenge in wildfire prediction (Jaafari & Pourghasemi, 2019).

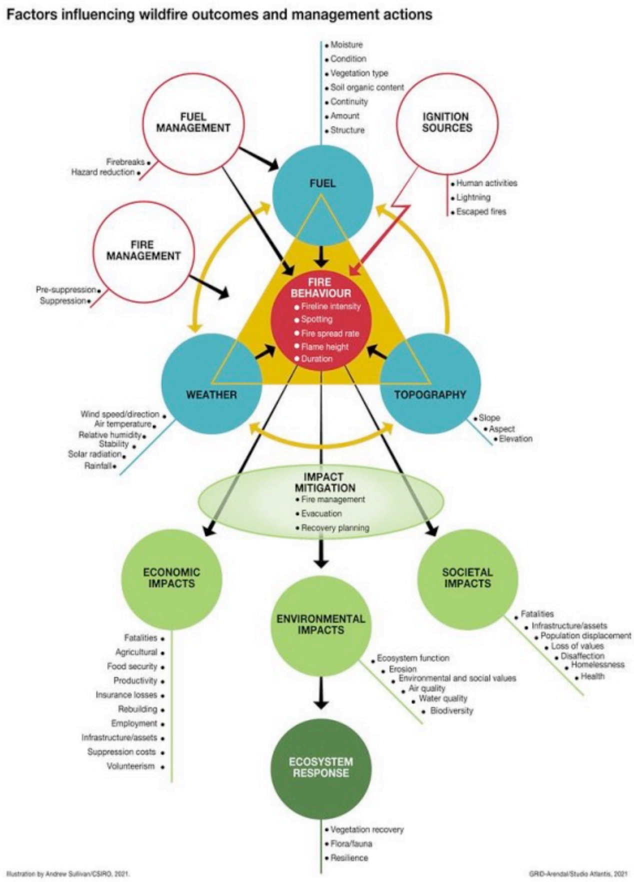


Figure 1: Factors influencing wildfire outcomes and management actions.

Regarding environmental factors that cause wildfires, regional fire patterns associated with natural ignition sources are traditionally referred to as "natural fire regimes". Regarding environmental factors, weather, fuel, and topography are the main causes of forest fire outbreaks, especially in the Mediterranean region. Natural fire regimes are primarily caused by the interaction of climate, topography, local microenvironment, and land use land cover change (LULC). Human intervention can also influence these regimes. There is an extensive discussion of the main drivers of changes in fire management regimes, with a focus on LULC and climate (Ganteaume et al., 2013; Koutsias et al., 2013). Some studies have documented that certain types of land cover such as grasslands, are closely associated with fire, while other land covers (e.g. cropland and orchards) are negatively associated (Baeza et al., 2002; Kocher & Butsic, 2017). Agricultural activities, such as burning land to restore pasture, are known to start fires and spread them into nearby shrublands and forests. However, the lack of ignitions is potentially associated with the presence of goats and sheep, most likely as a result of these animals' consumption of grass and bushes, which lowers the buildup of fine fuels (Romero-Calcerrada et al., 2008).

In the upcoming decades, vegetation, temperature, and fire dynamics may change because of land abandonment-related afforestation. The Mediterranean and Scandinavian countries in Europe have a larger chance of farmland abandonment in the near future because of continuing socioeconomic dynamics, so deforestation increases the frequency and severity of fire regimes (Terres et al., 2015; Ursino & Romano, 2014).

According to expert opinion and literature review, 15 adjustment factors for forest fire are slope degree, slope aspect, elevation, topographic wetness index (TWI), topographic position index (TPI), plan curvature, wind effect, annual temperature and rainfall, soil texture, distance to roads, rivers, and villages, normalized difference vegetation index (NDVI), and land use. The findings showed that factors related to land use, yearly rainfall, and proximity to highways were the primary causes of forest fires (Pourtaghi et al., 2016). Meteorological factors have a large impact on the occurrence and spread of fires in forests (Konca-Kędzierska & Pianko-Kluczyńska, 2018). Climate, meteorology, and environmental conditions cannot be ignored as they contribute to the occurrence, fire, and spread of accidental forest fires. For example, south-facing slopes within the forest provide ideal conditions for fires to occur due to high humidity and low soil moisture due to abundant sunlight (Kim et al., 2019). In the case of Iran, the factors that most influenced the occurrence of forest fires were precipitation and altitude (Jaafari & Pourghasemi, 2019). In Greece, analysis based on the period 1894–2010 revealed that while summer precipitation tended to drop and spring precipitation tended to increase the country's total annual precipitation showed a negative (albeit not statistically significant) long-term trend. The reason for this could be that spring precipitation promotes biomass productivity and permits the accumulation of fine fuel, whereas summer precipitation decreases the likelihood of fires by increasing fuel moisture, which inhibits the spread of fires (Koutsias et al., 2013). Furthermore, in Greece, between 1961 and 1997, there was a strong positive correlation between the prevalence of wildfires, the amount of land burned, and the drought. This could be explained by the length of time needed for the forest fuels to dry up and lose enough moisture content to ignite. The only factor influencing the frequency and severity of fires in Greece's Southern and Central districts—where there is the most fire activity—is the summer drought. The annual drought also becomes a deciding factor for the fire load in the more humid and less fire-prone areas of Northern and Western Greece (Dimitrakopoulos et al., 2011).

Forest fuels can be broadly divided into two categories: living and dead (Yebra et al., 2013). The amount of water in a fuel is referred to as its Fuel Moisture Content (FMC), and it is typically expressed as a percentage. Additionally, there are two classifications for FMC: Dead FMC (DFMC) and Live FMC (LFMC). Forest fire behavior and occurrence are significantly influenced by both FMC groups (Chuvieco et al., 2004). However, it is thought that DFMC has a bigger impact on fire behavior and vegetation flammability levels than LFMC (Jyoteeshkumar reddy et al., 2021). The primary reason for this is that dead fine fuels ignite more easily. The ignitability levels of the plants are thus significantly affected by changes in the moisture content of the fast-responding dead fine fuels(Boer et al., 2017; Dimitrakopoulos & Bemmerzouk, 2003). In consideration of the aforementioned claims, the literature suggests that DFMC is a better method for determining the flammability levels of forested regions. The DFMC was predicted to be between 6 and 7% at the time of ignitions, suggesting a high risk for major wildfires (Giannaros et al., 2022). Interpolation techniques, which typically result in large computation errors, are used to estimate the DFMC. Remotely sensed (RS) data with a spatial resolution of 1 km2 or finer could be employed as alternatives for the estimation of DFMC in order to get over this restriction. For the validation and subsequent estimation of DFMC from Automated Weather Stations (AWSs), it would be very beneficial to install new AWSs inside physical regions (forests, woodlands, etc.) (Dragozi et al., 2021).

Although drought worsens fire conditions, wind speed is the environmental factor that most influences areas burned by wildfires. In addition to drying soil and surface moisture, wind also has the ability to start sparks and fires to produce new fuel. When the wind picks up, it adds oxygen to the flame, heating the fuel in its path. When heat, dryness, and wind occur together, fires can start and spread quickly (Dimitrakopoulos et al., 2011; Naderpour et al., 2021).

Next, an alternative causal inference approach to assessing the effects of top-down weather and bottom-up fuel precursors on wildfires is presented. The wildfire drivers are divided into two groups: (i) top-down group, including maximum air temperature (Tmax), vapor pressure deficit (VPD), potential evaporation (ET0), wind speed (Wind) and aridity anomaly index (AAI) (ii) bottom-up group, including the fraction of photosynthetically active radiation (FPAR), gross primary production (GPP), normalized difference vegetation index (NDVI), enhanced vegetation index (EVI), and soil water deficit index (SWDI).

On wildfires, top-down dominance is more common than bottom-up dominance. In mid-latitudes, eastern Siberian boreal forests, and tropical rainforests, the top-down antecedents predominate. In savannahs in Australia and Africa, as well as in boreal forests in North America and Europe, the bottom-up predecessors predominate. This may be explained by the fact that high-intensity crown fires, which burn through more fuel, are more common in North American boreal forests, where fire-embracing black spruce forests predominate, whereas wildfires in eastern Siberia's fire-resistant species-dominated boreal forests tend to be low-intensity surface fires. In areas where bottom-up precursors predominate, seasonal or interannual forecasts are possible (Qu et al., 2023).

Anticipating the position and timing of upcoming storms and strikes is also very crucial to anticipate the incidence of flames, as lightning is the second most prevalent source of wildfires, after human causes, or even the primary cause of ignition in some places with extremely low population densities (Jain et al., 2020). Long-Continuing Currents (LCCs) are electrical currents in lightning that flow for more than a few tens of milliseconds and have the potential to cause fires. Using meteorological factors as a proxy, LCC lightning occurrence over Europe may be parameterized in atmospheric models. Future research can use this parameterization to improve the modeling of fire occurrence (Pérez-Invernón et al., 2021, 2023). Although lightning-induced fires are not common in countries around the Mediterranean Basin and other Mediterranean regions, the moisture content of the fuel has a significant impact on the likelihood of ignition (Ganteaume et al., 2013).

Climate change is another factor that should be considered; global LCC lightning flash rate has a rise of 41%. Wildfire regime changes are accelerating due to current global change. Changes in climate can lengthen the time that fuel is sufficiently dry to burn. The effects of an extended fire season on wildfire behavior are unknown. In fact, future fire seasons may be prolonged to the point that, in some areas, the fire may become active year-round (Duane et al., 2021; Pérez-Invernón et al., 2023).

In most cases, when it comes to predict fire occurrence without the use of AI, the classic Fire Weather Index (FWI) (Van Wagner, 1987) is used to anticipate the fire threat for the following day, nevertheless this index ignores human factors and vegetation-related fire causes and only considers meteorological conditions. Although FWI system was originally developed for boreal ecosystems, it is broadly used (de Jong et al., 2016; Di Giuseppe et al., 2020). FWI collects meteorological variables (such as temperature, humidity, and wind speed) to create unique index risk information that has been shown to be able to explain annual variation in wildfires. However, evidence from global fires suggests a new situation in which an unprecedented combination of conditions could lead to extreme wildfire events (Duane et al., 2021).

2.3 Fire Prediction using Artificial Intelligence

More complex models have replaced statistical analysis methods as the primary means of predicting the risk of forest fires. It has been demonstrated that machine learning algorithms can produce more accurate fire forecast findings (Bar Massada et al., 2013; Mohajane et al., 2021; Ngoc Thach et al., 2018).

While process-oriented global vegetation-fire models typically begin with a conceptual model, data-driven techniques seek to generate mathematical and computational models directly from the data. In data-driven approaches, a set of potential predictor variables is used to predict a response variable (here burned area, or fire counts) using machine learning algorithms, or evolutionary algorithms (e.g., genetic optimization). The significance of individual factors and the sensitivity of the response variable to the predictor variables enable the formation of a conceptual model of the system under study, provided that a sufficient data-driven model has been derived (Solomatine & Ostfeld, 2008).

In the last fifteen years, machine learning (ML) techniques have effectively supplanted conventional field-survey methods for predicting the susceptibility of forests to fires by clarifying the connection between past fire occurrences and various explanatory factors to forecast future fires (Jaafari et al., 2017). Although the complexity of wildfires often poses a modeling challenge, significant advances have been made in wildfire monitoring and observation, primarily due to increased availability and capabilities of remote sensing technologies. Additionally, improvements in numerical weather forecasting and climate models may result in smaller spatial resolutions, longer forecast lead times, and improved predictability of extreme fire weather events. Such developments make data-centric approaches to wildfire modeling a natural progression for many research questions, given sufficient data. As a result, interest in the use of ML techniques in wildfire science and management has increased in recent years (Bauer et al., 2015; Jain et al., 2020).

There are several issues and difficulties when using machine learning to predict the risk of fire. Complex interactions between fire causes that operate at many temporal and spatial scales and primarily interact nonlinearly are what create wildfires. The incidence of wildfires is inherently stochastic; the absence of a fire incident does not imply that there is no fire risk. Wildfires are physical processes that have a wide range of effects on both the environment and people. It is critical to understand what motivates the models' predictions to move beyond simple forecasting (Kondylatos et al., 2022).

Due to the variety of fire causes, the assessment of fire risk is made considerably more difficult. Both human and environmental variables must be modeled to determine what causes a fire to ignite. The likelihood of forest fires is generally influenced by human activity, not just by climatic elements like precipitation, elevation, topographic moisture index, and kind of forest, but also by socioeconomic factors like population density and distance from an urban area. The spatial distribution of fire probability is increasingly concentrated in or around cities, and forest fire probability shows strong correlations with anthropogenic variables over time (Ganteaume et al., 2013; Kim et al., 2019). Arson, smoking, hunting, stubble burning, picnics, shepherd fires, and other activities have been found to be the primary causes of forest fires globally (Mhawej et al., 2017). However, spatial and temporal modeling of these factors has often been considered a challenge. Higher population concentrations (population density) and elevation of the forest may indicate the presence of more human activity. Variables connected to humans, such as land cover and the distance from residential areas and roadways, were found to have the greatest influence (Kim et al., 2019; Pham et al., 2020). Several authors have tried to link human land-use variables such as socioeconomic status and demographics with wildland fire activity. Spatially referenced variables can now be more easily included into these models because to the availability of Geographic Information Systems (GIS) technology (Vilar et al., 2010).

The selection of a model for predicting the risk of forest fires is still up for debate. The diversity of training data from various regions has led to the identification of no single model or method that can capture fire behavior in all regions (Pham et al., 2020; Tan & Feng, 2023).

The most used ML techniques in wildfires include Random Forests, MaxEnt, Artificial Neural Networks, Decision Trees, Support Vector Machines, and Genetic Algorithms, so the main methods have been studied (Bot & Borges, 2022; Jain et al., 2020). Each method has its own strengths and weaknesses. The choice of method depends mainly on the specific problem and data characteristics. Different models predict wildfire probability and map wildfire danger zones differently. For instance, Deep Learning (DL) models use data to capture the nonlinear relationships between the environmental, meteorological, and human factors that cause fires. To evaluate the probability of fire outbreaks, fuel-related factors (NDVI, soil moisture, and relative humidity) should be used in conjunction with meteorological causes, as indicated by the correlations that arise from the DL models. The DL models create the physical reasoning behind the drivers of the forecasts (Kondylatos et al., 2022).

One of the main advantages of using ML techniques in wildfire prediction instead of the traditional methods (e.g. FWI) is that there is model transferability, which means that we can adjust the contributing factors if needed, for example, predicting fire in a different area with different meteorological and environmental characteristics, or in case of climate change. Basic prerequisite to use ML algorithms, in general, is the existence of sufficient data of high quality. Another important issue worth mentioning is the selection bias. The performance of ML algorithms is affected when datasets are heavily imbalanced or in case where there are variables missing. Explainable Artificial Intelligence (xAI) techniques such as feature importance analysis can help us identify the most critical features for wildfire prediction, reducing the computational burden of training models on irrelevant or redundant features, plus we can comprehend the model's decisions (Abdollahi & Pradhan, 2023).

Over the last years, researchers have also focused on hybrid and ensemble models to achieve greater prediction accuracy; that is using ML, geospatial analysis, and remote sensing imagery to pinpoint regions at risk of wildfires (Bot & Borges, 2022; Tan & Feng, 2023). Regardless the way we approach wildfires forecasting, computational time required for the modelling process should always be one of our primary concerns (Bot & Borges, 2022).

2.4 Data Pre-processing and Feature Engineering

The initial data utilized in this study was sourced from the official European Union data portal, (Temperature and Relative Humidity — 08:00 and 13:00 — T.E.C. - Data Europa EU, n.d.). Exploratory Data Analysis (EDA) is a crucial preliminary step, intending to maximize our insight through patterns, anomalies and correlations before creating our model. The specific dataset consists of 10038 rows, 7 columns and contains data on temperature and relative humidity, recorded at the 5 following locations:

- Paphos Airport
- Larnaca Airport
- Athalassa
- Limassol (New Port)
- Paralimni (Hospital)

In order to provide a comprehensive understanding of the environmental context within which the temperature and the relative humidity were collected, we present the locations of our sensors, indicated by red dots on the map (Figure 2), which shows the tree canopy height across the island.

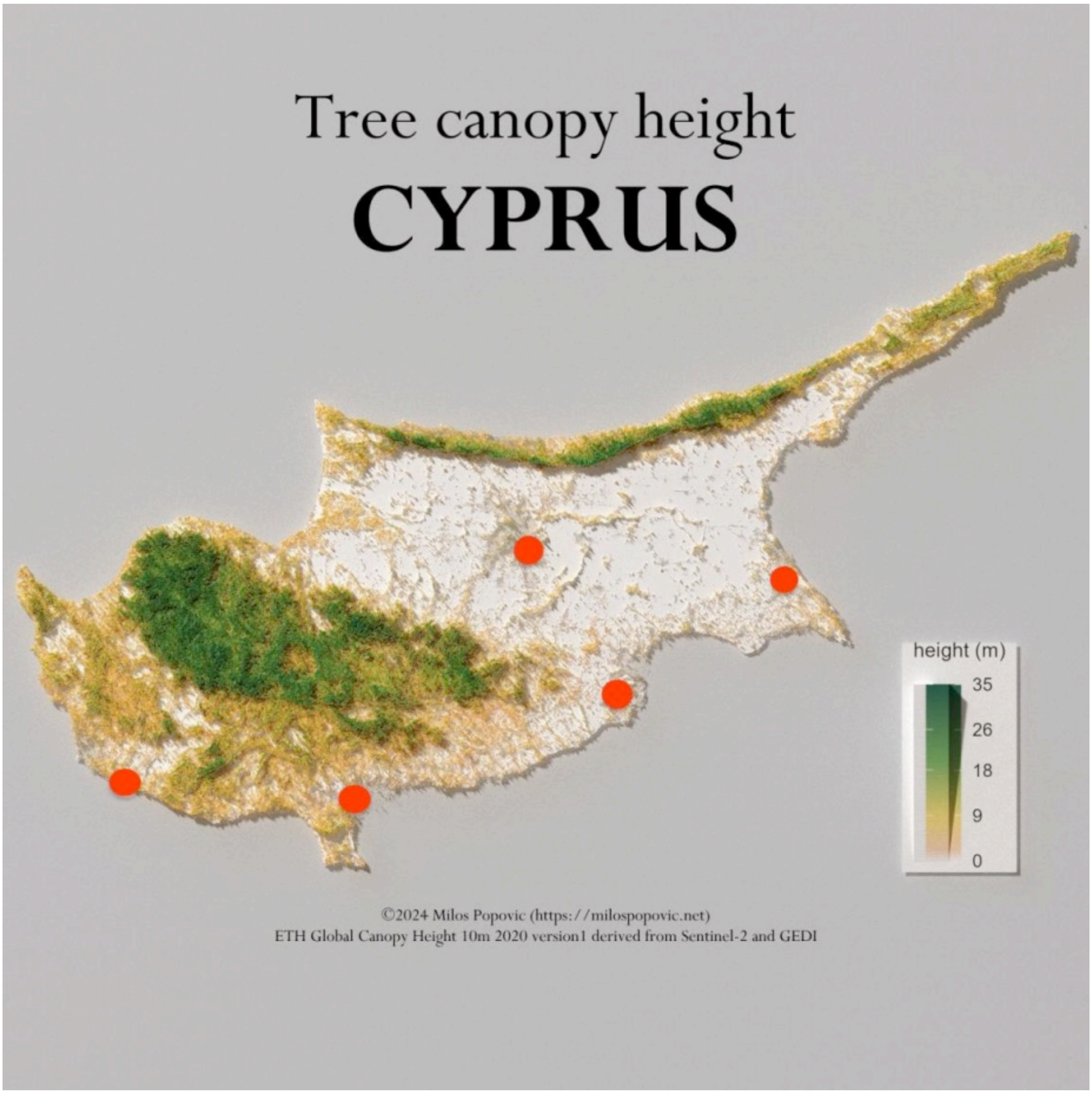


Figure 2: Tree canopy height.

It is important to mention that the map informs us that the sensors are not located close to forests, but rather close to buildup areas and croplands. This suggests that human activity might have a greater impact on our predictions compared to environmental factors. Additionally, our sensors are not placed in high altitudes, ensuring that the recorded climatic data is representative of conditions at lower elevations.

The dataset includes daily information from 2010 to 2018. Specifically, data for stations (a), (b) and (c) start at 1st of September 2010, whereas data for stations (d) and (e) start at 1st of October 2018. Our variables are mostly numerical (temperature and relative humidity), a datetime and a categorical (Location). For every day we have two sets of records (for 08:00 and 13:00 respectively), which means that we can check both times and compare which can give us a better prediction. Table 1 presents a slice of the dataframe that is used in the model.

Table 1: Data slice of Weather dataset.

	DATE	LOCATION	TEMP AT 8:00 (Celcius)	RELATIVE HUMIDITY AT 8:00	TEMP AT 13:00 (Celcius)	RELATIVE HUMIDITY AT 13:00	FIRE
0	40179	1	15.9	83.0	20.9	71	0
1	40180	1	14.9	90.0	21.9	70	0
2	40181	1	18.2	66.0	19.4	62	0
3	40182	1	18.1	68.0	19.2	67	0
4	40183	1	16.4	64.0	18.2	59	0

Luckily there is no missing data, however there are some outliers. In column Temperature at 08:00 there are values of 121.4 °C and 58 °C which seem to be unrealistic. In these specific days there is no indication of fire, so it seems to be data errors. Other than these everything seems to be reasonable.

There are only four features: Date, Location, Temperature and Relative Humidity, which is in conflict to what was mentioned earlier in literature review concerning the features we need to make a well based fire prediction – no data for land use and land cover, topography, precipitation, type of vegetation etc. Nevertheless, we will try to produce some worthwhile results.

Our dataset is pretty imbalanced, meaning that there are more days that there was no fire in comparison to the days that a fire occurred. This needs to be kept in mind later on, when we are about to select our metric score. Specifically, the dataset contains 2103 incidents of fire occurrence out of total 10038.

Feature selection is not an option in our case due to the lack of features, consequently, feature engineering seems to be unidirectional. Column Date shows a date but in a numeric format known as “serial number date”. Each integer represents the number of days since a specific base date – here 30th of December 1899. Apart from readability purposes, transforming dates to DDMMYYYY format is also preferred for creating visualizations and charts that suggest trends and patterns as we can create new columns based on month or day of the week.

Figure 3 shows the distribution of fires over the period from 2010 until 2018. Furthermore, Figure 4 presents a detailed breakdown of wildfire occurrences by month, offering a clearer view of the seasonal dynamics of fire behaviour. The data reveals a pronounced concentration of fire events during the summer and early fall months, typically between May and October. This seasonal trend aligns with established wildfire behaviour patterns, where extended periods of elevated temperatures, reduced precipitation, and low relative humidity contribute to drier vegetation and increased fuel flammability. Under such conditions, the likelihood of ignition and rapid fire spread is significantly heightened, emphasizing the critical role of climatic and environmental factors in influencing fire risk during this time of year.

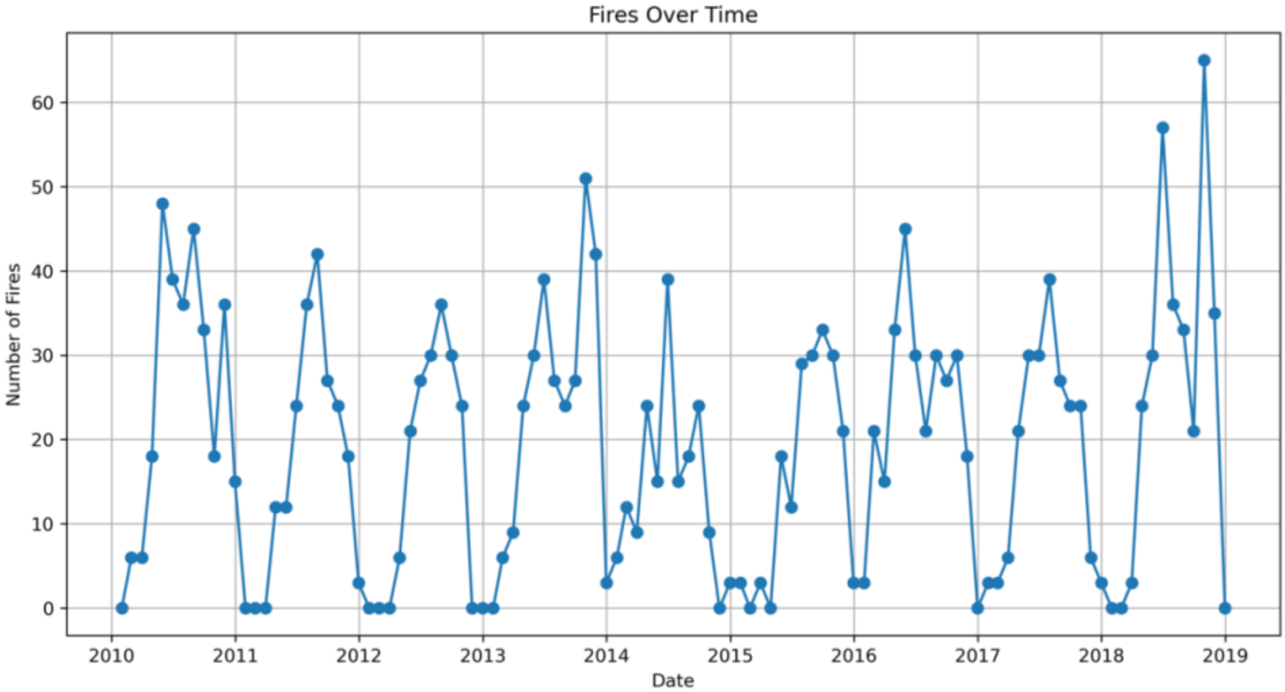


Figure 3: Fires over time.

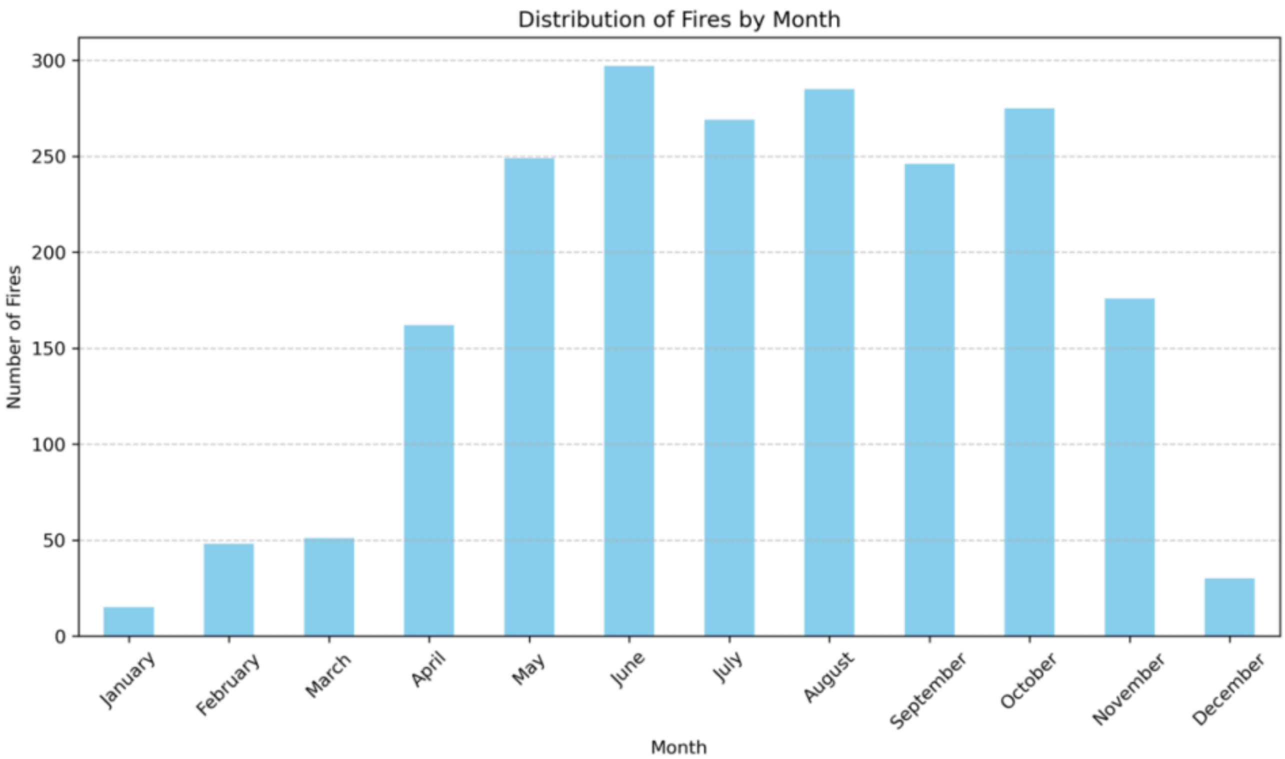


Figure 4: Distribution of fires by month

As shown in Table 1, the dataset has temperature and humidity readings for two times in the day, mainly 08:00 in the morning and 13:00 in midday. Separating the dataset in two, one for each time of the day, we get pretty much the same information concerning feature correlation based on different time (Figure 5, Figure 6).

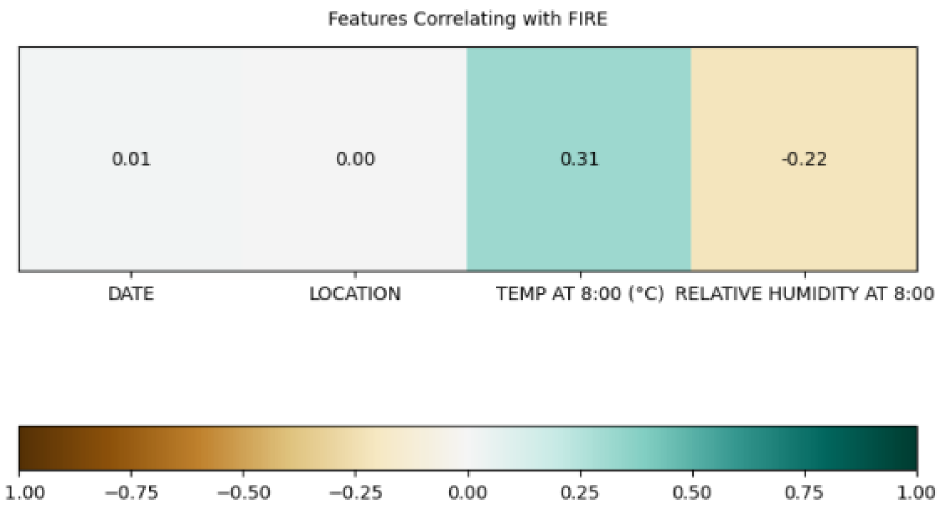


Figure 5: Feature correlation at 08:00.

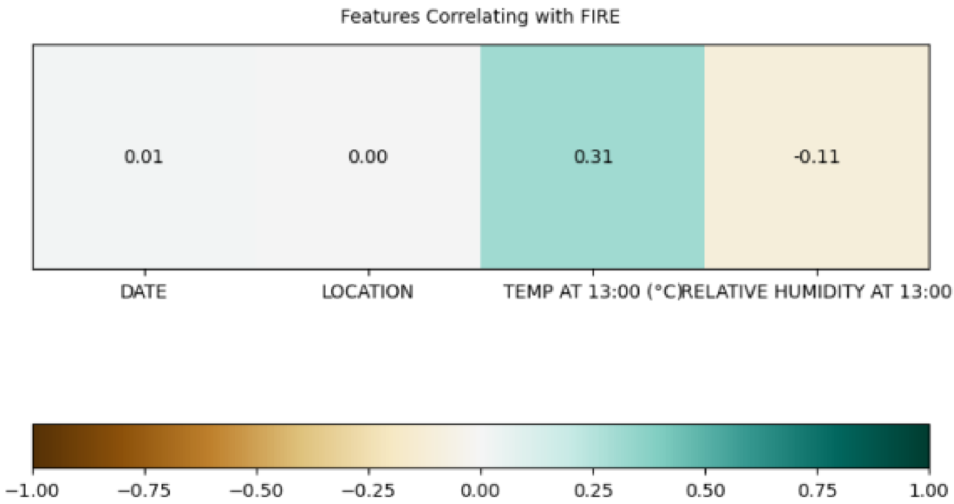


Figure 6: Feature correlation at 13:00.

Naturally -from what we know from bibliography- temperature has a positive correlation with fire occurrences whereas relative humidity shows a moderate negative correlation suggesting that the higher the temperature and the lower the relative humidity the more likely for a fire outburst. Date and Location do not seem to affect fire incidents. The aforementioned claim is reinforced by the following distributions Figure 7 – extreme temperatures and humidity is not so common, and this explains why we don't get so many fires when humidity is low and fire is high.

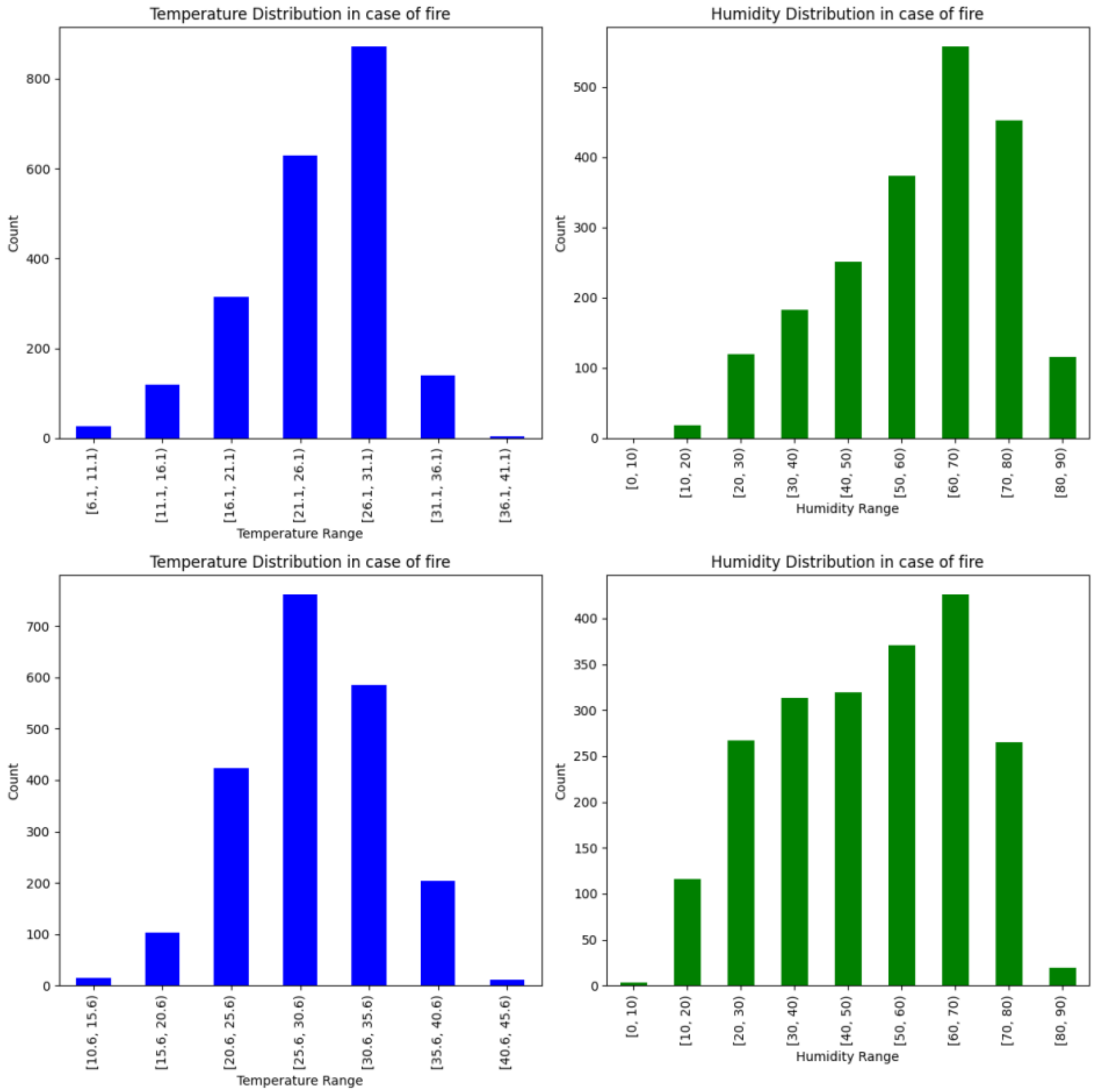


Figure 7: Temperature and Humidity distribution in case of fire

Performing optimization in Logistic Regression (LR) and training our data we get same accuracy for both hours (Table 2).

Table 2: Accuracy of Logistic regression.

Dataset	**Accuracy using LR**
08:00	0.7892
13:00	0.7886

Likewise, using Extreme Gradient Boosting (XGB) we get similar results (Table 3).

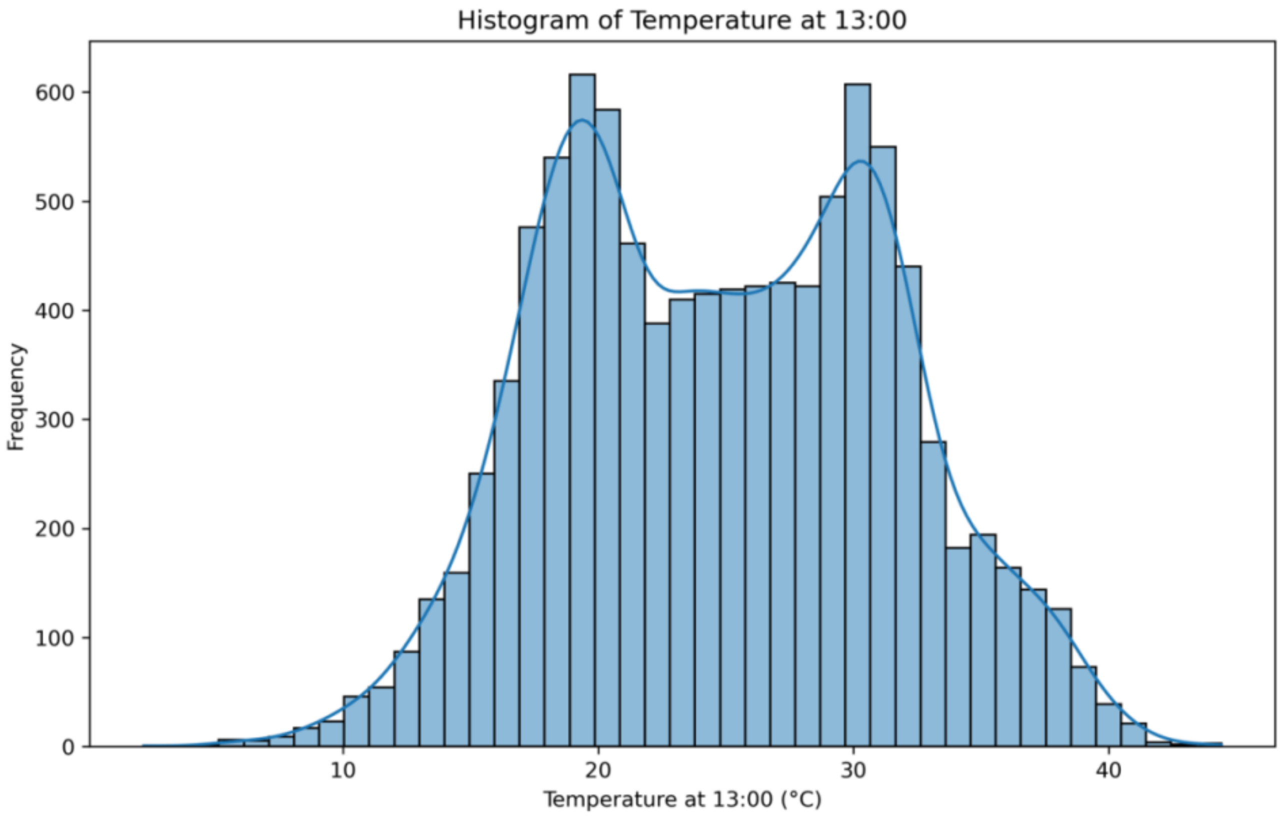
Table 3: Accuracy of XGBoost.

Dataset	Accuracy using XGB
08:00	0.7805
13:00	0.7795

Since there is no difference in results whether we use data at 08:00 or 13:00, we select data without outliers, that is data concerning 13:00.

2.5 Model Selection

Before selecting a ML model for predicting fire occurrences, our next step in preprocessing the data is to scale the temperature values. In this way we ensure that the values are scaled to a fixed range, likely to improve the model's performance. In this case we will use Min-Max Scaling to transform the temperature values to a fixed range, between 0 and 1. Min – Max scaling is sensitive to outliers but the dataset we have has no outliers (minimum temperature is 2.2 °C and the maximum is 44.4 °C). We choose Min - Max scaling because our data distribution is non-Gaussian. Standardization is not used because it is more suitable for normally distributed data.



Scaling will be applied after splitting the data into train and test sets, so that we prevent data leakage – which means information from the test set affects the training process. Table 4 presents a slice of the final dataframe.

Table 4: Scaled dataframe.

DATE	LOCATION	TEMPERATURE	REL. HUMID.	MONTH	DAY	FIRE
2010-01-01	1	0.44312796208530	0.71	1	4	0
2010-01-02	1	0.46682464454976	0.7	1	5	0
2010-01-03	1	0.40758293838862	0.62	1	6	0
2010-01-04	1	0.40284360189573	0.67	1	0	0
2010-01-05	1	0.37914691943127	0.59	1	1	0

Extreme Gradient Boosting (XGBoost) is a popular ML algorithm because of its efficiency and performance in both classification and regression tasks. It is designed to use parallel and distributed computing to improve the speed of computation and handle large-scale data. XGBoost builds an ensemble of decision trees in a sequential manner, where each tree aims to correct the errors of its predecessor. Gradient boosting involves training multiple weak learners in sequence. Each subsequent model focuses on the residual errors made by the previous models, reducing the overall error iteratively. XGBoost uses a technique called tree pruning to remove branches that do not contribute significantly to the model's performance, which improves computational performance. It also includes regularization terms -both Lasso (L1) and Ridge (L2), to prevent overfitting. XGBoost is commonly used for fire prediction because of its high accuracy and efficiency in handling large datasets.

When dealing with time series data or data involving dates in general, there are certain features which exhibit periodic behaviour. For instance, days of the week, days of the month, and moths of the year are cyclical. Traditional numerical representation of these features may mislead ML models since they don't capture this cyclical nature. For example, January and December represented numerically as 1 and 12, however they are consecutive. To handle this, we will transform the aforementioned features by using sine and cosine functions, which represent cyclical data. In this way we ensure that the cyclical relationship is preserved. Following we see the formulas we use to make the transformations.

In the previous step, LR and XGB models have already been used, however we can run a series of quick tests with different models so we can narrow our choices to select our final model. Data exploration has shown that we have an imbalanced dataset – as non-fire instances dominate over fire instances. Usually, we can overcome this issue by using class weights or by generating synthetic data using Synthetic Minority Over-sampling Technique (SMOTE), however in our case the accuracy did not improve (Table 5).

Table 5: Model accuracies.

Model	**Accuracy**	**Accuracy using weights**	**Accuracy using SMOTE**
Random Forest	0.769	0.782	0.798
XGBoost	0.798	0.798	0.725
SVM	0.788	0.796	0.498
KNN	0.767	0.761	0.773
MLP	0.788	0.796	0.510

It is obvious that none of the models vastly improves, in contrary, when we use SMOTE Support Vector Classifier and Multi-Layer Perceptron display significant drop in their performance. We will select XGBoost as the model of choice, even though its accuracy with SMOTE is lower, its base performance is high, which suggests that it is less dependent on oversampling techniques. Furthermore, we apply transformations for periodic variables.

Table 6: Final dataframe.

LOCATION	TEMP (°C)	REL. HUM.	Year	DayOfMonth sin	DayOfMonth cos	DayOfWeek sin	DayOfWeek cos	Month sin	Month cos	FIRE
1	0.4431…	0.71	2010	0.2012…	0.9795…	-0.43388…	-0.9009…	0.4999…	0.8660…	0
1	0.4668…	0.7	2010	0.3943…	0.9189…	-0.9749…	-0.2225…	0.4999…	0.8660…	0
1	0.4075…	0.62	2010	0.5712…	0.8207…	-0.7818…	0.6234…	0.4999…	0.8660…	0
1	0.4028…	0.67	2010	0.7247…	0.6889…	0.0	1.0	0.4999…	0.8660…	0

1	0.3791	0.59	2010	0.8486	0.5289	0.7818	0.6234	0.4999	0.8660	0
	…			…	…	…	…	…	…	

After all the transformations we applied, we end up with the dataframe in Table 6 and the accuracy score we get is 0.8303, there is a significant raise in our accuracy. The next step is performing a hyperparameter optimizing of our model.

2.6 Feature Importance in Fire Prediction Model

While developing the ML model it was crucial to identify the variables which had significantly impacted our predictions. The following graph depicts the importance of each feature when using the final XGBoost model.

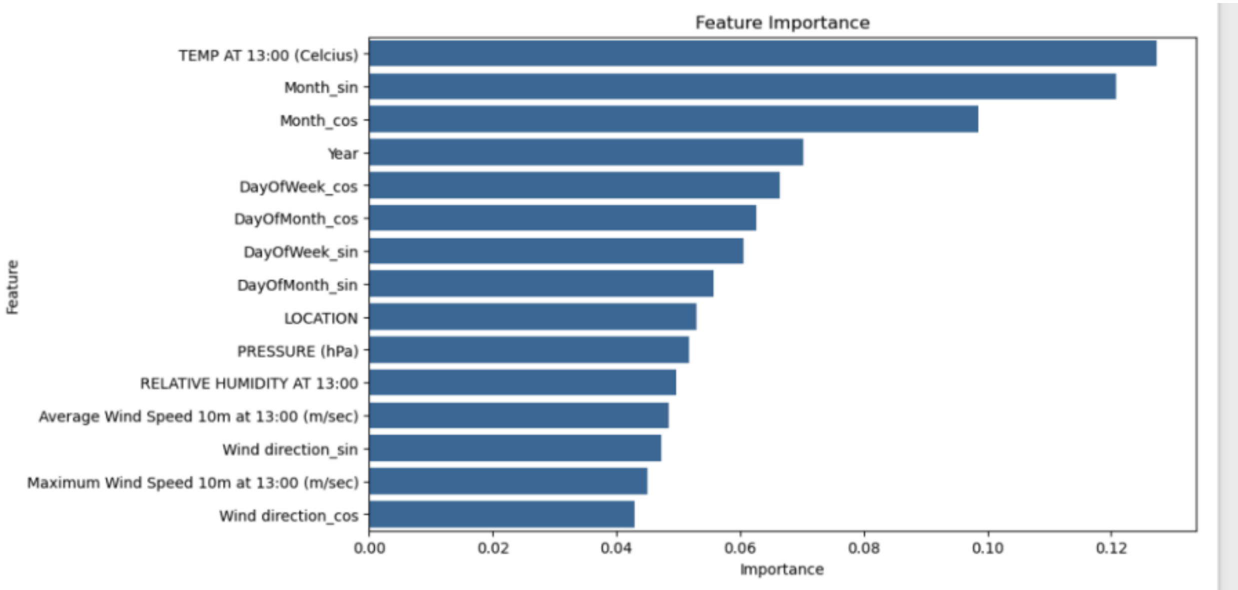


Figure 8: Feature importance.

The Temperature emerged apparently as the most significant variable, indicating that high temperatures correlate with increased fire occurrences. This finding aligns with common sense and the bibliography which claims that elevated temperatures enhance the flammability of fuel. Month transformations are highly significant as well, suggesting that certain seasons of the year have higher tendency for fires due to climatic conditions. Actually, Month_sin and Month_cos combined score is higher than Temperature's score.

The Year variable was important as well, highlighting long-term trends in fire risk, which could mean climate change or even changes of land usage. Similarly, the sine and cosine transformations of the Day of the week and Day of the Month affect our predictions, as they capture weekly and monthly patters in fire occurrences, presumably influenced by human activities such as outdoor activities in weekends. The Location variable and the rest below- Pressure, Relative Humidity, Wind Speed and Wind Direction were less significant. Their lower importance suggests that they might contribute noise to the model rather than enhancing its accuracy.

Consequently, these features can be even considered redundant as they introduce unnecessary complexity, increasing the dimensionality.

The feature importance analysis underscores the complex interaction of meteorological, temporal and geographic factors in fire prediction. However, it emphasizes the need for careful consideration of which variables to include. Improved forecasting models can lead to more effective fire management strategies, which will ultimately reduce the destructive effects of wildfires.

2.7 Challenges and Limitations

The primary challenge was the limited data from AWSs in Cyprus. As seen in Figure 9, there are 53 AWSs, but data was only available from five stations. This limited data coverage posed significant challenges. Those five AWSs are located close to urban areas rather than forested areas, which are generally more prone to wildfires. Consequently, the model's predictions are biased towards conditions that are common in urban settings. The absence of data from forested regions sets a limit to the model's accuracy when predicting fire occurrences in high-risk regions.

Figure 9: Automated weather stations in Cyprus.

Another critical issue confronted was the inadequate quantity of features available for the model training. Key factors such as rainfall precipitation, and fuel content (DFMC and LFMC) unfortunately weren't available. These variables are fundamental for an accurate fire prediction as they straightforwardly impact the likelihood of a fire. The absence of these decisive variables limited the model's ability to capture environmental and meteorological conditions in which fire is about to burst. Overall, this resulted in a less comprehensive model.

Last but not least, an extra challenge was the occurrence of deliberate, human-caused fires. It is intrinsically difficult to predict deliberate fires – mostly caused by arson, based solely on meteorological and environmental data. These incidents are not driven by natural factors; therefore they cannot be measured, neither forecasted. If we knew which fires were intentional, our model would be better at predicting naturally caused fires, however it would still not be able to predict arsons.

3. Fire Detection Module

A key component of the fire system was selecting the appropriate sensors to ensure the system received the necessary data. Wind speed and direction are crucial factors in forest fire applications that aid in fire behaviour prediction, fire spread patterns, safety of firefighters and air quality and smoke management. Smoke sensors (CO_2, Temperature and Humidity) aid in alerting authorities and communities, assessment of environmental impact, support for firefighting operations and monitoring fire progress.

The use of CO_2 sensor networks for early wildfire warning has been validated in multiple research studies, demonstrating their potential to significantly enhance fire detection capabilities [11], [12]. These sensors are capable of continuously monitoring atmospheric carbon dioxide levels, which can rapidly increase during the early stages of a wildfire due to the combustion of biomass. By deploying a network of such sensors across high-risk areas, researchers have shown that it is possible to detect fires more quickly than with traditional methods such as satellite imaging or lookout towers. Additionally, sensor networks offer the advantage of real-time, ground-level data collection, which enables faster emergency response and more precise localization of fire outbreaks. This approach not only improves situational awareness for firefighting efforts but also contributes to the broader goal of minimizing environmental damage and protecting communities at risk.

Collaborating with the forestry department, we identified two locations that were blind spots relating to the surrounding lookout towers and installed a number of sensors to detect fire. The CO_2 data is transmitted to the fire detection module which uses the fire prediction data with the CO_2 values to determine if a fire has started near the sensor. When the fire risk prediction is high then a lower CO_2 threshold will trigger an event otherwise a higher CO_2 level would be required. This significantly improves our ability to detect fires early during high-risk conditions.

3.1 Fire Module Composite Sensor Selection and Parameters

This section details all composite sensors chosen for the Green-HIT project, these components play a pivotal role in enhancing the efficiency and effectiveness of forest management practices, offering tailored solutions for data retrieval, incident validation, and environmental monitoring, leveraging advanced technologies such as LoRaWAN and/or Satellite communication.

Selection of market sensor was done based on requirements provided for the creation of the fire module. Wind speed and direction are crucial factors in forest fire applications that aid in fire behaviour prediction, fire spread patterns, safety of firefighters and air quality and smoke management. Smoke sensors (CO_2, Temperature and Humidity) aid in alerting authorities and communities, assessment of environmental impact, support for firefighting operations and monitoring fire progress. Temperature and humidity are also measured on the weather station level.

The below tables list the parameters of the sensors selected for the installations.

Table 7: Seeed SenseCAP S2120 8-in-1 weather station sensor parameters.

Seeed SenseCAP S2120 8-in-1 Weather Station						
Temperature	Range	-40°C to + 80°C	Accuracy	±0.5 °C	Resolution	0.1 °C
Humidity	Range	1 to 99 %RH	Accuracy	±3%	Resolution	1%RH
Rainfall	Range	0 to 450 mm/h	Accuracy	±7%	Resolution	0.254 mm/h
Pressure	Range	540 to 1100hPa	Accuracy	±5hPa	Resolution	1hPa
Wind Speed	Range	0 to 50m/s	Accuracy	±0.5m/s	Resolution	0.1m/s
Wind Direction	Range	0 to 360°	Accuracy	±8°	Resolution	1°
Light Intensity	Range	0 to 200000lux	Accuracy	±5%	Resolution	1lux
UV Index	Range	0 to 16	Accuracy	±10%	Resolution	0.1

Table 8: Smoke sensor parameters.

CO2 Sensors		
	Milesight EM500 Smoke Sensor	**Seeed SenseCAP S2103 Smoke Sensor**
CO2 Range	400 - 5000 ppm	400 - 10000 ppm
CO2 Accuracy	± (30 ppm + 3 % of reading) (0°C - 50°C, 0 - 85%RH)	±(30 ppm +3% of reading) (extended range ±10% of reading)
CO2 Resolution	1 ppm	1 ppm
Temperature Range	-30°C to + 70°C	-40°C to + 85°C
Temperature Accuracy	0°C to + 70°C (+/- 0.3°C), -30°C to 0°C (+/- 0.6°C)	±0.2 °C
Temperature Resolution	0.1°	0.01 °C
Humidity Range	0% to 100% RH	0% to 100% RH
Humidity Accuracy	10% to 90% RH (+/- 3%), below 10% and above 90% RH (+/- 5%)	±1.8 %RH
Humidity Resolution	0.5% RH	0.01% RH

3.2 Sensor Installation

Sensor installation was done in multiple locations in 2 areas in accordance with requirements. The areas are the *Troodos forest* and the *Ayios Nikolaos* areas. These were chosen based on prior research done by partners of the project to select high risk locations.

The installation of the sensors was done in cooperation with the Forest Department of Cyprus, the department identified locations in the area that had the following criteria regarding the fire module:

- Identified blind spots that are not observable from fire stations.
- High risk of fire breakout areas either identified from experience or previous incidents.

The table below details the sensors installed and their quantities.

Table 9: Hard installation locations and quantities.

Hardware	Location	Quantity
Milesight EM500 Smoke Sensor	Troodos	40
Seeed SenseCAP S2103 Smoke Sensor	Ayios Nikolaos	50
Seeed SenseCAP S2120 Weather Station	Both	4 (2 each)

CO_2 sensors were installed in clusters in those locations to account for effective CO_2 coverage, Weather Station were placed in central locations in the area to optimally cover it for atmospheric measurements, particularly wind speed and direction.

Figure 10: Installed sensors (Weather Station left, EM500 centre, SenseCAP S2103 right).

4. Fire Propagation Module

To simulate wildfire spread in real-world terrain, it is essential to continuously determine new geospatial coordinates from the location a Fire Starts and is Detected towards its general movement propagation. This module calculates the general location of movement of the **next fire propagation point** based on a given starting location's coordinates, distance (ideal range and prediction distance of next movement location of fire - 150M), and directional bearing (*typically aligned with wind direction sensed from closest weather station*). The result can be used to extract topographic elevation data for slope and terrain analysis via external APIs that will be used to calculate the **slope** between the two points to further calculate slope factor, which will in turn be used as a crucial parameter to calculate the Rate of Spread of the identified Fire.

4.1 Fire propagation algorithm

The algorithm performs **spherical trigonometric calculations** to compute a new latitude and longitude from an initial geographic coordinate, accounting for Earth's curvature.

Given:

- Initial coordinates: Fire Sensor, sensing high levels of Co2 indicating Fire.
- Distance to propagate: 150 meters from starting location of Fire.
- Directional bearing: Degrees° of current wind (*where* North = 0°/360°, East = 90°, South = 180, West = 270).

The steps include:

1. **Convert Directional Bearing Degrees to Radians**:

   Trigonometric functions in Python require angles in radians.

2. **Apply Great-Circle Navigation Formulae to Coordinates**:

   Latitude change: *Eq. (1)*.

$$\Delta\phi = \frac{d \cdot \cos(\theta)}{R}$$

   Longitude change: *Eq. (2)*.

$$\Delta\lambda = \frac{d \cdot \sin(\theta)}{R \cdot \cos(\phi)}$$

3. Where:
    - d is the distance in meters,
    - θ is the propagation angle in radians,
    - R is Earth's radius (*approximated as 6,371,000 meters*),
    - φ is the original latitude in radians.
4. **Convert Back to Directional Bearing Degrees**:
   After calculating the deltas, the script converts them to degrees and adds them to the original coordinates to obtain the new calculated predicted fire front position.
5. **Elevation Query**:
   The new coordinates are used to construct a URL for querying elevation data from the **OpenTopodata API** using the EUDEM 25m resolution dataset:
   https://api.opentopodata.org/v1/eudem25m?locations=LAT,LON

This module allows fire spread simulations to move incrementally across geographic space, dynamically updating the fire’s location and fetching real-time elevation data. This enables **terrain-aware spread modelling**, crucial for predicting slope factor effect on fire behavior in mountainous or complex landscapes.

4.2 Identifying Closest Weather Station to Fire Using the Haversine Formula

Accurate distance measurement between geospatial coordinates is essential in fire monitoring systems, particularly when integrating data from distributed **deployed weather stations**, **strategically scattered fire sensors**, and **IoT-based edge devices**. In order to use the most appropriate live data from multiple weather stations distributed across the terrain, this script uses the Fires Starting Location and determines the closest weather station deployed, in order to identify the most appropriate *wind speed, direction, barometric pressure* of the weather conditions closest to the active Fire. To estimate the direct ground distance between such points on the Earth's surface, this module employs the **Haversine formula**, which accounts for the Earth's curvature.

Description of the Algorithm:

Given two points:

- **Weather Station Coordinates**: [Longitude] [Latitude] – List of all Weather Stations
- **Live Fire Sensor Coordinates**: [Longitude] [Latitude] – Triggered Sensor, Fire = 1

The script follows these steps:

1. **Convert Coordinates to Radians**:
   All latitude and longitude values are converted from degrees to radians for trigonometric operations.
2. **Compute Differences**: *Eq. (3)*.

$$\Delta\phi = \text{lat2\_rad} - \text{lat1\_rad}, \quad \Delta\lambda = \text{lon2\_rad} - \text{lon1\_rad}$$

3. **Apply the Haversine Formula**: *Eq. (4)*.

$$a = \sin^2\left(\frac{\Delta\phi}{2}\right) + \cos(\phi_1)\cdot\cos(\phi_2)\cdot\sin^2\left(\frac{\Delta\lambda}{2}\right)$$

$$c = 2\cdot\arctan2(\sqrt{a}, \sqrt{1-a})$$

$$\text{Distance} = R\cdot c$$

Where:

- R=6371.0 km is the Earth's radius,
- c is the central angle between the points in radians.

4. **Output**: The result is the **great-circle distance** in **kilometers** between the two points.

This method is vital in:

- Determining proximity between fire detections and local weather conditions,
- Configuring sensor coverage areas,
- Correlating environmental data with detected fire events for propagation modelling.

By accurately measuring these distances, the model enhances both **data fusion** and **spatial reasoning** in fire monitoring systems.

4.3 Terrain Slope Angle Calculation for Fire Spread Prediction

Slope is a major contributing factor in wildfire behavior, influencing both the rate and direction of spread. Fires tend to move faster uphill due to preheating of fuels and slower downhill. This module calculates the **slope angle** between two geospatial points based on their elevation difference and horizontal separation, enabling integration with slope-based fire propagation models (e.g., Van Wagner's correction).

Description of the Algorithm:

Given:

- **Elevation at Point 1 (Fire Origin)**
- **Elevation at Point 2 (Predicted Fire Movement Point Calculated)**
- **Horizontal Distance Between Points**: 150 meters

1. **Compute Vertical Elevation Difference**: *Eq. (5)*.

$$\Delta h = \text{elevation\_point2} - \text{elevation\_point1}$$

2. **Calculate Slope Angle (Radians)**: *Eq. (6)*.

$$\theta_{\text{rad}} = \arctan\left(\frac{\Delta h}{d}\right)$$

3. **Convert to Degrees**: *Eq. (7)*.

$$\theta_{\text{deg}} = \theta_{\text{rad}} \times \left(\frac{180}{\pi}\right)$$

4. **Optional Conversion**: The script reconverts the result from degrees back to radians (slope_angle_radians) to maintain compatibility with other modules that may require angle input in radians.

This calculated slope angle feeds directly into the **Van Wagner slope factor model**, enabling a **quantitative correction** of the Rate of Spread (**ROS**). Accurate slope determination is essential for realistic simulation of fire behaviour over complex terrain, especially when paired with elevation datasets such as those retrieved via OpenTopodata.

4.4 Fire Propagation – ROS (Rate of Spread) Calculation Modelling Module

To estimate the dynamic spread of wildfire across varying terrain and environmental conditions, we implemented a Python-based calculation for **Rate of Spread (ROS)** adjustment. The script reflects the impact of two primary influencing factors – **wind** and **slope** – on a given baseline or "*flat*" **ROS** value.

Description of the Algorithm:

The function calculate_ros receives three parameters:

flat_ros: The baseline rate of fire spread over flat terrain (measured in meters per minute),

wind_factor: A dimensionless coefficient accounting for wind-driven acceleration of the fire front, Calcuclated @ INDEX

slope_factor: A dimensionless coefficient representing how slope influences uphill or downhill fire spread. Calcuclated @ INDEX

The **adjusted ROS** is calculated using the empirical formula: *Eq. (8)*.

$$\text{Adjusted ROS} = \text{flat\_ros} \times (1 + \text{wind\_factor} + \text{slope\_factor})$$

This formula linearly amplifies the base ROS by incorporating the combined effects of wind and slope, both of which are known to significantly increase fire propagation speed.

- The flat ROS is hardcoded as 0.985 m/min,
- Wind and slope factors are set computed and substituted in this formula from two other corresponding module – wind_Factor_Calculator and slope_Factor_Calculator_Positive_Negative respectively,
- The output prints the **adjusted ROS**.

Use in Simulation / Risk Assessment and Fire Propagation Module:

This ROS model forms a fundamental component in wildfire simulation systems, helping to estimate how fast and in what direction a fire might propagate under specific conditions. The simplicity of the implementation allows it to be modularly extended or integrated with more complex geospatial fire models or real-time sensor data inputs in emergency response systems.

4.5 Wind Factor Calculation for ROS Calculation Modelling Module

Wind is a critical environmental variable influencing wildfire behaviour, significantly accelerating the rate and direction of fire spread. To quantify this influence, we implemented a wind factor calculation model based on an exponential response to wind speed.

Description of the Algorithm:

The calculate_wind_factor function estimates the wind contribution to fire propagation using the following formula: *Eq. (9)*.

$$\text{Wind Factor} = e^{(k \cdot V)}$$

Where:

- V is the wind speed in meters per second (m/s), received from the nearest weather station deployed in the Cyprus forest (using H
- k is an empirically chosen **wind influence coefficient** (default: 0.05),
- e is Euler's number (≈ 2.718).

This exponential model reflects the **nonlinear impact** of increasing wind speeds on fire dynamics, where small increases in wind can lead to disproportionately larger increases in spread rate.

This factor is later used to scale the **Rate of Spread (ROS)** in the main propagation model, emphasizing how intensifying winds enhance wildfire mobility.

Application Context:

The wind factor function is modular and can be integrated with real-time meteorological data from weather stations, satellite feeds, or IoT sensors deployed in wildfire-prone regions. Adjustments to the coefficient k can be made to tailor the model to specific vegetation types or regional fire behaviour patterns, offering flexibility and calibration capabilities for different simulation scenarios.

4.6 Slope Factor Calculation Using Van Wagner's Equation for ROS Calculation Modelling Module

Topographic slope plays a critical role in wildfire behaviour, influencing the speed and intensity of fire spread. Uphill slopes can accelerate fire movement due to preheating of fuels, while downhill slopes tend to have a dampening effect. To model this terrain-dependent behaviour, we adopted an approach based on **Van Wagner's 1988 fire behaviour equations**, which are widely referenced in wildfire science.

Description of the Algorithm:

The function van_wagner_slope_factor computes a **slope correction factor** based on the **angle of inclination or declination** of terrain. The model is segmented into two distinct regimes:

1. **Negative Slopes (Declining Terrain: -45° to 0°):**

Fire **slows down on downhill slopes** due to reduced radiant and convective heat reaching the unburned fuel. However, the slowdown isn't linear or guaranteed. Specifically, **for slopes steeper than -22° (i.e... steeper downhill)**, the fire may still maintain momentum due to:

- **Falling burning debris**, such as rolling logs or flaming pinecones, which can **ignite fuels downslope**.
- **Wind effects** and **chimneying** in valleys, which may counteract the downward slope effect.

In Van Wagner's model, **slope factors for downhill angles greater than -22° return close to 1.0**, meaning the fire behaves nearly as if it were on flat terrain — a realistic representation of how **downhill fires can still be aggressive**, especially in forested regions.

For mild negative slopes (≥ **-22°**), a **quadratic reduction** is applied: *Eq. (10)*.

$$\text{Slope Factor} = 1 - 0.36 \cdot \left(\frac{\text{slope\_angle}}{-22}\right)^2$$

This represents a **gradual decrease** in the effective ROS as terrain slopes downward.

For steeper declines (< **-22°**), the slope factor **resets to unity [1.0]**, suggesting no further suppression of ROS.

2. **Positive Slopes (Inclining Terrain: 0° to 31°):**

Wildfires tend to **propagate faster uphill** because flames and convective heat rise, preheating the unburned fuel located upslope. This **preheating effect** dries and ignites vegetation more quickly, leading to **exponential increases in the Rate of Spread (ROS)** as slope increases. This phenomenon becomes more pronounced as the slope angle steepens, particularly between 0° and 31°.

For positive slopes, Van Wagner's **empirical exponential formula** is used: *Eq. (11)*.

$$\text{Slope Factor} = \exp\left(3.533 \cdot \tan(\theta)^{1.2}\right)$$

where θ is the slope angle in radians. This reflects the **accelerating effect** of uphill slopes on fire spread, increasing rapidly with steepness.

The function includes input validation to ensure the slope angle remains within the domain supported by Van Wagner's model: **-45° to 31°**.

Application Context:

This slope correction factor is used to modify the base ROS in the fire propagation model. When combined with wind and vegetation models, this allows for a comprehensive simulation of wildfire dynamics over real-world terrain. The modular design of the function allows integration into GIS-based fire modelling systems or real-time emergency response tools.

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