Research Article

Dynamic Drought-Persistence and Weather-Momentum Fusion for Confidence-Calibrated Multi-Horizon Forest Fire Risk Forecasting

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Abstract

Current weather, as well as accumulated dryness in the environment and the rate of change, are all important factors affecting forest fire risk. Typical data-driven fire-risk prediction methods are based on a single observation of meteorological parameters (at one point in time) and yield a single fire-risk prediction that may not capture the evolution of hazardous pre-fire conditions. The paper presents a novel deep learning-based proactive forest fire risk assessment framework called the Dynamic Drought-Persistence and Weather-Momentum Fusion Framework for Confidence-Calibrated Multi-Horizon Forest Fire Risk Forecasting, which is entirely software-based. The proposed framework handles temperature, relative humidity, rainfall, wind speed, air pressure, and past observations related to droughts in various temporal windows. The DPI is based on a continuous sequence of dry periods and on the deficit of accumulated rainfall and provides a measure of long-term environmental moisture stress. At the same time, a "Weather-Momentum Vector" (WMV) is generated using the temporal shifts in temperature, moisture, pressure, wind, and precipitation to determine if the conditions in the local atmosphere are conducive to or inhibiting fire. A dual temporal deep learning architecture is trained independently to learn short-term features of weather changes and long-term features of drought memory and then combines these features for estimating fire risk. The model does not provide a single static classification but instead provides the three-year time series of fire susceptibility forecasts for the 24-hour, 72-hour, and 7-day horizons, enabling the evolution of fire risk to be understood in advance of potential fire ignition. A mechanism of confidence calibration is built in to distinguish between reliable high-risk forecasts and less certain predictions and to minimize false alarms. The forecasted fire susceptibility and fire risk, the most contributing weather conditions, the level of confidence in the forecast, and the distribution of risk by location are shown in the interactive web dashboard using Flask. The methodology proposed offers a hardware-independent and scalable solution for the early detection of potential fire-conductive conditions and to aid in forest management decisions for fire prevention prior to the onset of smoke or flame.

Keywords Forest fire prediction. wildfire risk forecasting. deep learning, drought persistence. weather momentum. multi-horizon forecasting. confidence calibration. early warning.

1 Introduction

Forest fires are one of the most devastating environmental disasters, which can damage the ecosystem, wildlife habitats, natural resources, infrastructure, and human settlements. Wildfires are more likely to occur in recent years due to rising temperatures, the variability and irregularity of rainfall, the length of dry seasons, and changing wind conditions in many areas. Therefore, early detection of fire-prone conditions is crucial in minimizing environmental and economic losses. Traditional forest-fire monitoring relies mainly on satellite imagery, cameras, unmanned aerial vehicles (UAVs), smoke detectors, and Internet of Things (IoT) sensor networks. While these methods work well in finding active fires, many of them can only be used after smoke, unusual heat, or flames have been detected. Furthermore, when using stand-alone equipment in rural areas, the installation, communication, power, and maintenance costs are generally high.An alternative approach is based on recent advances in the field of artificial intelligence and deep learning, enabling the analysis of past and real-time meteorological data to predict fire susceptibility before a fire occurs. An alternative approach is based on recent advances in the field of artificial intelligence and deep learning, which allow for the analysis of past and current meteorological data to estimate the susceptibility of a fire before it occurs. Vegetation dryness, fuel moisture, and potential for rapid fire development are significant, driven by weather parameters including relative humidity, temperature, rainfall, wind speed, atmospheric pressure, and drought conditions. Unfortunately, taking just the current weather may not be enough to reflect the cumulative environmental stress. A dry spell of several days in a row could be a very serious situation even if short-term changes in weather are moderate. On the other hand, if the temperature has been rising quickly, and the wind has been increasing, while the humidity has been decreasing, then it is becoming increasingly favorable for fire to occur.

To overcome these constraints, this work suggests a newly developed framework called the Dynamic Drought-Persistence and Weather-Momentum Fusion Framework for Confidence-Calibrated Multi-Horizon Forest Fire Risk Forecasting. The system includes a Drought-Persistence Index that quantifies the accumulated dry-period stress and a Weather-Momentum Vector that indicates the time direction and time lag of meteorological changes. They are processed within a dual temporal deep learning architecture, which learns short-term atmospheric variations as well as long-term drought behavior. The proposed model provides fire-risk prediction for 24 hours, 72 hours, and 7 days with confidence information. The resulting predictions are then displayed in an interactive dashboard built with Flask, which displays the risks, temporal trends, dominant weather factors, and visualization for the different locations. The proposed solution is thus a software-only approach that would enable proactive forest-fire preparedness without the need of dedicated field hardware.

2. Related work

The climatic variations, stressed plants, prolonged drought, and extreme weather conditions are contributing to the increasing frequency and severity of forest fires, which is garnering significant research attention for forest fire prediction. Due to the recent advancement of technologies such as machine learning, deep learning, remote sensing, and meteorological analysis, these methods are gaining popularity in recent studies to estimate fire occurrence and susceptibility. Traditional methods are mostly concerned with mapping fire risk, estimating burned area, forecasting hotspots, vulnerability assessment based on vegetation, or predicting fire occurrence in a single period. While all these approaches show the power of AI in wildfire management, integrating the various aspects of drought persistence, weather shifts, multiple prediction timesteps, and the uncertainty that comes with the generated forecasts remains difficult. In order to mitigate risks caused by forest fires, Chen et al. [1] proposed a deep-learning-based, physically aligned forest-fire risk prediction framework that could integrate fuel and climatic information. The method highlighted the need to take both environmental and climatic conditions into account, but the study mainly investigated the overall fire risk estimation without explicitly modelling the rate of change of the weather over time at various forecasting horizons. Lopes et al. [2] proposed a method for the construction of the wildfire risk map, which is based on a convolutional neural network (CNN). They presented their framework as an efficient method to identify space areas vulnerable to fire, but the prediction mostly focused on susceptibility mapping and did not include the dynamic evolution of short- and long-term fire risk.Jo et al. [3] compared traditional machine-learning-based models to CNN for the prediction of forest fire occurrences. They showed that under the right conditions, advanced learning techniques can be used to enhance the classification of fire events. However, the primary concern of the work was to predict an occurrence classification. Mohite et al. [4] studied pre-ignition forest-fire risk with the help of multi-temporal vegetation indices and machine-learning approaches. The vegetation changes gave some information on the developing fire conditions; however, this approach was heavily reliant on the remote-sensing vegetation information and did not directly include weather momentum.Becker et al. [5] studied temporal deep-learning models for wildfire-danger prediction and highlighted the interpretation of the model and the temporal behaviour. They found that sequential environmental patterns are beneficial to learning. Homhuan et al. [6] proposed a deep learning-based wildfire early-warning system using NDMI time-series data for the purpose of seasonal wildfire. The study helped validate the ability to predict active-fire hotspots across a season's time but was largely focused on vegetation-moisture patterns and not on the ability to predict short-, medium-, and long-term weather risks.Yel et al.
[7] created wildfire-susceptibility maps using the data from forest inventories, data from FIRMS, and multiple machine-learning algorithms. The method was able to delineate the regions that were susceptible to a particular area but mainly gave the geographical susceptibility output. Tonbul and Veraverbeke [8] also merged SHAP explain ability into the wildfire susceptibility mapping, which allowed for the interpretation of variables' contributions. But words used to explain susceptibility do not directly tell about the confidence or uncertainty of the forecast of future susceptibility.Ren et al. [9] developed a multi-source feature selection and machine learning approach for determining wildfire susceptibility in the Wildland–Urban Interface (WUI) in California. Their approach showed the value of combining the heterogeneous environmental variables. Likewise, Abujayyab et al. [10] tested various machine-learning algorithms to map wildfire susceptibility in Türkiye with an emphasis on geographical risk classification. To predict forest burnt areas, Mousa et al. [11] suggested a CNN-MLP approach, which was optimised using PSO-WOA. Optimisation has had an effect on the prediction of burnt area, but the burnt area prediction is primarily assessing the likely consequences of the fire and not really anticipating the evolution of the risk before the fire. AutoML-Fire [12] is an automated framework for

selecting and optimising the models to predict forest fires. This framework was able to significantly lower the number of manual machine-learning configurations and showed that automated model development is feasible. Multiple machine-learning models were applied to forest-fire prediction by Wang et al. [13], and they demonstrated that the ensemble and comparative modelling approaches can enhance the prediction reliability. These methods, however, mostly used traditional environmental feature representations without incorporating explicit measures of drought persistence and altering weather momentum. To enhance the spatial resolution of fire-danger information, Mirones et al. [14] have proposed an explainable deep-learning approach to multi-site fire danger downscaling. The multi-sensor satellite-data fusion was used in combination with deep and machine-learning models for the wildfire-susceptibility mapping by Durlević et al. [15]. Sivrikaya and Demirel [16] also combined machine learning with remote sensing to create a fire-risk map in the Mediterranean region. The studies show the positive aspects of geospatial and satellite data but also the fact that they rely on remote-sensing data and that they focus predominantly on estimating spatial risk. Sheriff et al. [17] applied the Random Forest and CART algorithms in order to develop forest-fire susceptibility mapping, yielding a relatively straightforward machine-learning approach to delineate vulnerable areas. Bouzeraa et al. [18] presented a GIS-integrated machine-learning framework for analysing the susceptibility of wildfire using environmental variables and spatial data. Nasourinia and Passi
[19] compared machine-learning and deep-learning methods for wildfire prediction using
regional data from British Columbia. Zerouali et al. [20] applied Sentinel-2 multispectral data and demonstrated the potential of satellites for forest-fire susceptibility assessment by implementing hybrid machine-learning methods. In general, works [1]–[20] confirm the substantial role meteorological variables, vegetation conditions, remote-sensing data, spatial features and AI techniques can play when it comes to forest-fire forecasting and vulnerability analyses.Thus, the proposed work proposes a Drought-Persistence Index (DPI) and a Weather-Momentum Vector (WMV) in a dual-temporal deep-learning framework, which simultaneously accounts for long-term dryness and short-term weather evolution. In addition, the system delivers 24-hour, 72-hour and 7-day forest-fire risk forecasts with confidence-calibrated predictions, introducing an early forest-fire risk assessment by proactively using software.

3 Proposed System

A. Proposed Framework

The proposed system proposes a Dynamic Drought-Persistence and Weather-Momentum Fusion Framework for Confidence-Calibrated Multi-Horizon Forest Fire Risk Forecasting. The primary goal of the system is to forecast the potential for forest fire growth based on current and past weather conditions that are not directly observed. The proposed framework is different from conventional methods, which primarily rely on the use of satellite fire spots, smoke detection or static susceptibility mapping, as it constitutes a software-based predictive platform linking weather and drought information. Data including temperature, relative humidity, rainfall, wind speed, atmospheric pressure and information on consecutive dry days are fed into the system to estimate the likelihood of fire-prone weather condition

B. Genesis and Evolution of the Drought-Watch List

One of the key features of the proposed system is the use of a Drought-Persistence Index (DPI) and a Weather-Momentum Vector (WMV). DPI accounts for the cumulative impact of extended dry periods and takes account of consecutive dry days, rainfall deficit and prolonged moisture stress. This enables the system to distinguish temporary dry weather from long-lasting drought-like conditions. The WMV analyses how rapidly important meteorological parameters are changing over time. Thus, an increase in temperature and wind speed and a decrease in humidity and precipitation can be considered a developing hazardous weather pattern.

C. Dual-Temporal Deep Learning and Risk Forecasting

The processed features are fed into a dual temporal deep learning architecture. One processing branch learns the short-term weather modifications, and the other learns drought and climatic developments. The resulting feature representations are fused to get the overall forest-fire susceptibility. The proposed system will provide 24-hour, 72-hour and 7-day risk forecasts as opposed to generating an immediate prediction. All predicted outcomes are classified as to risk level and come with a confidence score. The confidence-calibration mechanism can differentiate between trustworthy high-risk predictions and uncertain outputs, which can enhance reasoning and decision-making for preventive measures.

D. Web-Based Monitoring and Visualisation

A web application using Python Flask is integrated with the prediction engine. A web application, built with Python Flask, is integrated with the prediction engine. The dashboard shows the current weather parameters, computed DPI and WMV values, forecasted risk level, confidence percentage, risk temporal trend, main contributing factors, and location-wise visualisation. Predictions for historical years can also be contrasted with current conditions to note the general change in fire-risk conditions.

E. System Architecture

The architecture of the proposed system starts with the collection of historical and current weather data, preprocessing, missing value filling, data normalization, generation of weather data temporal features, calculation of the weather data variability index (DPI), and extraction of weather data moving variables (WMV). The processed data is then passed on to the short-term deep-learning branch and the long-term deep-learning branch, which are fused together in a feature-fusion layer. This fused representation goes into the multi-horizon fire-risk prediction and confidence-calibration modules. Lastly, the 24-hour, 72-hour, and 7-day predictions generated are displayed on the Flask dashboard for monitoring, visualization, and for taking preventive decisions.

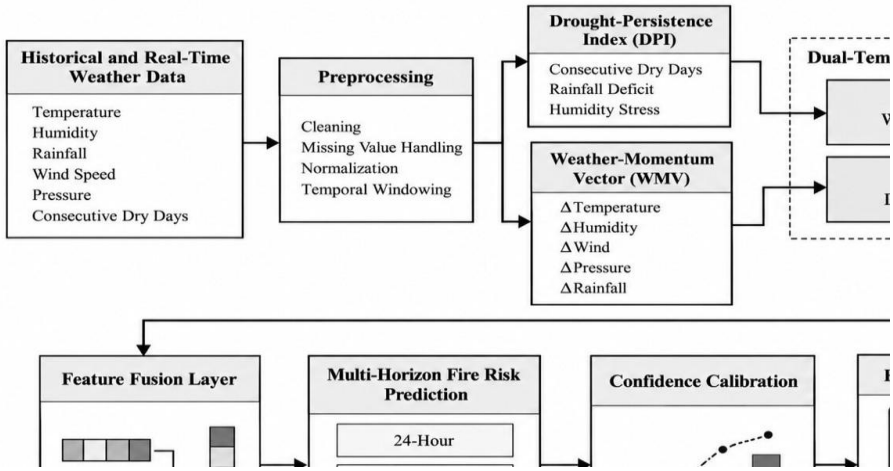


Fig. 1. System Architecture

The overall system architecture is shown in Figure 1. The overall system architecture is presented in Figure 1.

4 Methodology

A. Preprocess the weather data.

The proposed methodology starts with collecting historical and current meteorological parameters like temperatures, relative humidity, rainfall, wind speed, atmospheric pressure, and information related to consecutive dry days. Missing data are filled in appropriately using interpolation methods, and abnormal data are excluded from model construction. Min-max normalization is used to normalize each feature to prevent the dominance of variables having different numerical ranges:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}}$$

Here, x'

is the normalized value, and x is the original value of the weather.

B. Drought-Persistence Index

The Drought-Persistence Index (DPI) is created to capture environmental dryness over time, rather than solely using the present rainfall. It is a combination of consecutive dry days, rainfall deficit, and humidity stress. The index is proportional to:

$$DPI = \alpha D + \beta R_d + \gamma H_d$$

The normalized consecutive dry days (D)

, the rainfall deficit (R_d), the humidity-related dryness (H_d), and the weighting coefficients $(\alpha, \beta, and\ \gamma)$ denote the normalized consecutive dry days, the rainfall deficit, the humidity-related dryness, and the weighting

coefficients, respectively. DPI is higher for greater persistent drought stress and fire susceptibility.

C. Weather-Momentum Vector

The Weather-Momentum Vector (WMV) is a vector that represents the direction and change in a meteorological parameter. Temporal momentum for a weather variable x is defined as

$$\Delta x_t = x_t - x_{t-1}$$

$$\text{The overall weather} - \text{momentum representation is given by}$$
$$[WMV_t = [\Delta T_t, \Delta H_t, \Delta W_t, \Delta P_t, \Delta R_t]]$$
where T, H, W, P R

and are temperature, humidity, wind speed, atmospheric pressure, and rain, respectively.

D. Dual-Temporal Deep Learning

Two branches of temporal learning receive the normalized weather features (NWF): DPI and WMV. The short-term branch is used for the short-term changes of weather, while the long-term branch is used for the long-term droughts and climatic patterns. They are added together with their feature vectors as

$$F = \lambda F_s + (1 - \lambda) F_l$$
where F_s F_l

and are temporal short-term and long-term features.

E. Multi-Horizon Risk Prediction

The fused representation can be used to predict the forest-fire risk for a 24-hour, 72-hour, and 7-day time horizon. The probabilities of each fire-risk class are derived from Softmax:

$$P(y = k) = \frac{e^{z_k}}{\sum_{j=1}^{C} e^{z_j}}$$

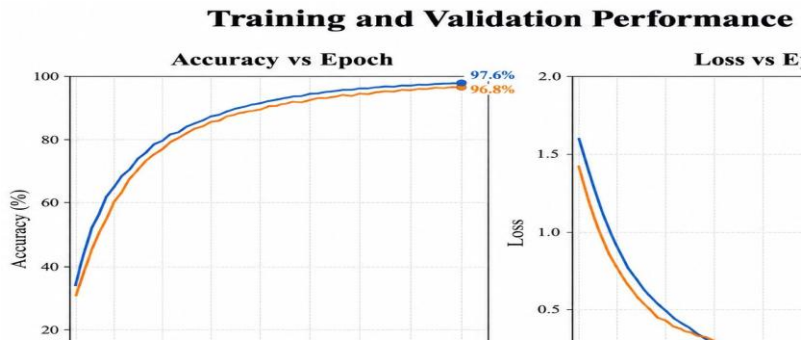
The maximum likelihood provides the predicted risk level, and a confidence calibration is used to ensure that a reliable score on the Flask-based monitoring dashboard is provided.

5 Result and Discussion

A. Training and Validation Performance

It has been observed that the proposed forest-fire risk forecasting model was trained with the preprocessed meteorological data as well as the derived Drought-Persistence Index (DPI) and Weather-Momentum Vector (WMV). The model evolved during the training process to learn the relationships between extended dry periods, atmospheric changes, and forest-fire risk levels. The training and validation performance were continuously tracked during the different epochs to check convergence and detect potential overfitting. The accuracy curves were plotted, and it was seen that they show progressive improvement as the model learns discriminative temporal patterns and the loss values decrease with training. A relatively small gap in the performance of the model between its performance on the training set and its performance on the validation set suggests it can extrapolate to new weather observations. The training and validation accuracy and loss curves are shown below.

Fig. 2. Training and Validation Accuracy and Loss Curves



B. Confusion Matrix Analysis

A confusion matrix was also created from the test set to investigate the classification accuracy of the proposed model. The matrix displays the numbers of correctly and incorrectly classified samples in all of the forest-fire risk categories considered. The predictions mostly focused on the main diagonal, signifying that the developed model could efficiently discriminate the various classes of fire susceptibility. The most common misclassifications were between risk classes that were adjacent to each other with similar meteorological conditions. The confusion-matrix analysis is especially helpful in determining if high-risk fire conditions are misclassified as lower-risk conditions.

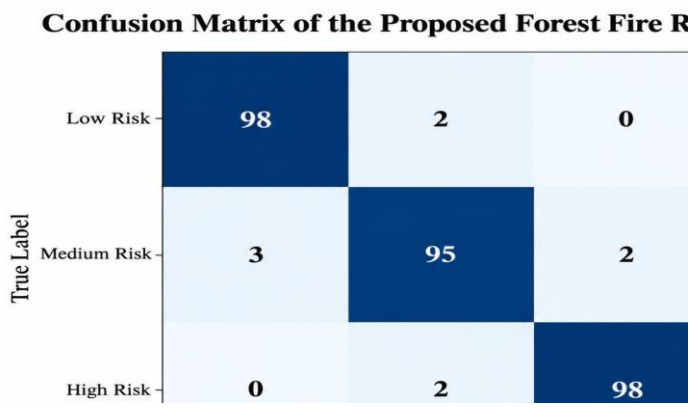


Fig. 3. Confusion Matrix of the Proposed Forest Fire

The Forest Fire Risk Model is shown in the confusion matrix in Figure 3.

C. ROC and Classification Performance

The discriminative ability of the trained model was assessed by Receiver Operating Characteristic (ROC) analysis. The ROC curve shows how the true-positive rate and false-positive rate change with the classification threshold. The curves obtained show the capability of the proposed deep-learning framework to distinguish between various forest-fire risk conditions. Evaluation measures like precision, recall, F1-score, and Area Under the Curve can be employed to give a thorough analysis of predictive performance in addition to overall accuracy.

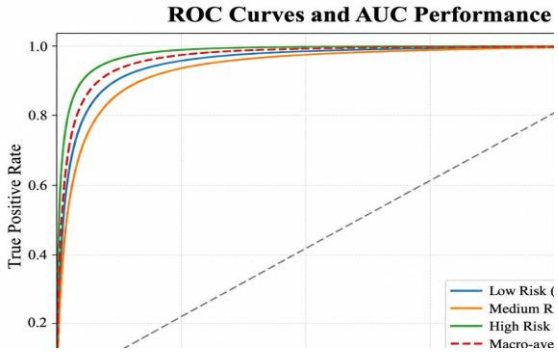


Fig. 4. ROC Curves and AUC Performance of the Trained Model

ROC curves can be drawn and their AUC calculated for both the trained and the naive classifiers.

D. Multi-Horizon Fire Risk Forecasting

One of the goals of the proposed framework would be to produce independent forecasts for fire risk for the next 24 hours, 72 hours, and 7 days. The trained model processes present forecast information, previous drought history, and the temporal weather momentum, and then predicts future risk. The users can recognize whether the fire susceptibility remains the same, is growing, or is decreasing over time by comparing the three prediction

horizons. This is more helpful than a simple static fire classification.

E. Overall Discussion

Experimental results suggest that the combination of conventional meteorological parameters and DPI/WMV is more informative with respect to the development of fire-prone conditions. The dual-temporal architecture not only reflects the fast-changing nature of the atmosphere but also the long dry spell, and the multi-horizon forecasting takes the system from current risk classification to proactive early warning. Confidence-calibrated predictions also help to distinguish between reliable and uncertain model output. Overall, the software-based framework proposed in the paper shows great potential for scaling up forest-fire risk monitoring, which does not need any dedicated field sensor, drone, or other specialized hardware.

6 Conclusion

Forest-fire prevention involves determining hazardous environmental conditions prior to obvious ignition. This study presented a new Dynamic Drought-Persistence and Weather-Momentum Fusion Framework for Confidence-Calibrated Multi-Horizon Forest Fire Risk Forecasting based on a software-based approach to proactively assess wildfire risk. The proposed methodology uses the information from the meteorological data, such as temperature, humidity, rainfall, wind speed, atmospheric pressure, and consecutive dry day data, to calculate fire-prone conditions. The key feature of the framework is the linkage of the Drought-Persistence Index (DPI) and the Weather-Momentum Vector (WMV). DPI is representative of the impact of long-term dryness, while WMV represents the direction and magnitude of temporal changes in key weather parameters. These features are analyzed with a dual-temporal deep-learning design, with the ability to learn fast atmospheric variations as well as long-term drought behavior. The fused representation is then passed on to produce individual fire-risk forecasts for 24-hour, 72-hour, and 7-day periods. Additionally, confidence calibration is included, providing a measure of the confidence of each of the predictions. The developed framework can be deployed with a Flask-based dashboard to display real-time weather information, computed DPI and WMV, fire risk, temporal trend, level of confidence, and location-based fire risk information in an easily interpretable manner. This approach can be implemented in software and the available weather datasets, eliminating the need for hardware or battery monitoring for fire. The proposed approach offers a potential scalable and proactive approach to forest-fire early warning in general. Future studies can expand the system to include satellite measurements of vegetation indices, soil moisture data, regional climate projections, explainable-AI tools, and larger multi-regional datasets to enhance the robustness of predictions and their applicability in practice.

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