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Review

Machine Learning and Deep Learning for Wildfire Spread Prediction: A Review

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Abstract: The increasing frequency and intensity of wildfires highlight the need to develop more efficient tools for firefighting and management, particularly in the field of wildfire spread prediction. Classical wildfire spread models have relied on mathematical and empirical approaches, which have trouble capturing the complexity of fire dynamics and suffer from poor flexibility and static assumptions. The emergence of machine learning (ML) and, more specifically, deep learning (DL) has introduced new techniques that significantly enhance prediction accuracy. ML models, such as support vector machines and ensemble models, use tabular data points to identify patterns and predict fire behavior. However, these models often struggle with the dynamic nature of wildfires. In contrast, DL approaches, such as convolutional neural networks (CNNs) and convolutional recurrent networks (CRNs), excel at handling the spatiotemporal complexities of wildfire data. CNNs are particularly effective at analyzing spatial data from satellite imagery, while CRNs are suited for both spatial and sequential data, making them highly performant in predicting fire behavior. This paper presents a systematic review of recent ML and DL techniques developed for wildfire spread prediction, detailing the commonly used datasets, the improvements achieved, and the limitations of current methods. It also outlines future research directions to address these challenges, emphasizing the potential for DL to play an important role in wildfire management and mitigation strategies.

Keywords: fire spread; fire modeling; wildfire; machine learning; deep learning

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1. Introduction

Wildfires have become a global hazard. They can cause severe damage to flora, fauna, and human habitats. Moreover, they are more frequent and intense due to climatic change. Even though the total area burned globally may decrease, fire behavior is worsening in various regions, with significant consequences for carbon storage and increased human vulnerability to wildfire disasters [1]. Current research underscores four main sections of wildfire risk management: fire prevention and mitigation, preparedness, response, and recovery phases [2]. In this context, to help authorities prevent and mitigate wildfires, multiple approaches have been developed to model fire behavior or predict fire spread. The earliest methods for predicting wildfire spread, such as the case in the Canadian Forest Fire Behavior Prediction System (FBP) [3], relied on empirical and mathematical techniques, which involved creating rules for modeling the spreading process. For example, Alexandridis et al. [4] simulated the dynamics of forest fire spread on a mountainous landscape proposed using a Cellular Automata model, a mathematical model based on rules. They considered factors such as the type and density of vegetation, the wind speed and direction, and the spotting phenomenon.

More recent techniques focus on machine learning and deep learning approaches, which stand to achieve promising performances. For example, Zheng et al. [5] combined the Extreme Machine Learning (EML) model and the classical Cellular Automaton (CA) model to simulate forest fire spread. Khanmohammadi et al. [6] tested several machine learning models to predict grassland fire spread, and concluded that linear support vector regression, exponential Gaussian process regression, boosted trees, and bilayered neural network models are the most efficient. With deep learning and multimodal data, fire-predicting models have become more and more performant. Marjani et al. [7] attained an accuracy of 98.6% with a multi-kernel convolutional neural network using remote-sensing and multimodal data. Masrur et al. [8] proposed the Convolutional Long Short-Term Memory (ConvLSTM) model with self-attention and predicted fire spread with an F1-score of 96%.

To the best of our knowledge, there is a clear gap in the literature regarding comprehensive reviews focusing solely on machine learning and deep learning models applied to wildfire spread prediction. Jain et al. [9] presented an overview and a review of popular ML approaches used in wildfire science as broadly categorized into six problem domains, including fuels characterization, fire detection, and mapping; fire weather and climate change; fire occurrence, susceptibility, and risk; fire behavior prediction; fire effects; and fire management. Bot and Borges [10] reviewed the applications of machine learning techniques for wildfire management decision support including wildfire spread ML techniques.

In this paper, we conduct a systematic review of ML and DL approaches to modeling fire behavior and predicting the spread of wildfires. We also present the most popular datasets used for these tasks and discuss the main challenges and limitations of these techniques. In comparison to previous reviews, our paper contributes as follows:

- It systematically analyzes recent machine learning and deep learning models used for fire behavior modeling and wildfire spread prediction.
- It highlights the most popular datasets (tabular and remote-sensing) to train and test ML and DL models for fire spread prediction.
- It discusses the challenges and limitations of these models, including the limits of these techniques, the integration of explainability and transparency in these models, the design of real-time and lightweight models, model generalizability, and the improvement of datasets and metrics.

As illustrated in Figure 1, the remainder of the review is structured as follows: Section 2 explains the methodology followed in conducting this review. Section 3 gives an overview of commonly used metrics in wildfire spread prediction. Section 4 compares classical methods to ML and DL techniques. Section 5 introduces the ML techniques used for wildfire spread prediction. Section 6 delves into the DL techniques categorized into convolutional neural networks (CNNs), convolutional recurrent networks (CRNs) and time series models, transformers, reinforcement learning (RL) models, and graph neural networks (GNNs). Section 7 illustrates the popular datasets for wildfire spread prediction. Section 8 critically summarizes and discusses the limits and challenges of these ML and DL techniques, the explainability of the models, real-time and lightweight models, model generalizability, and the limits of the existing datasets and metrics. Finally, Section 9 concludes the review, emphasizing future research directions.

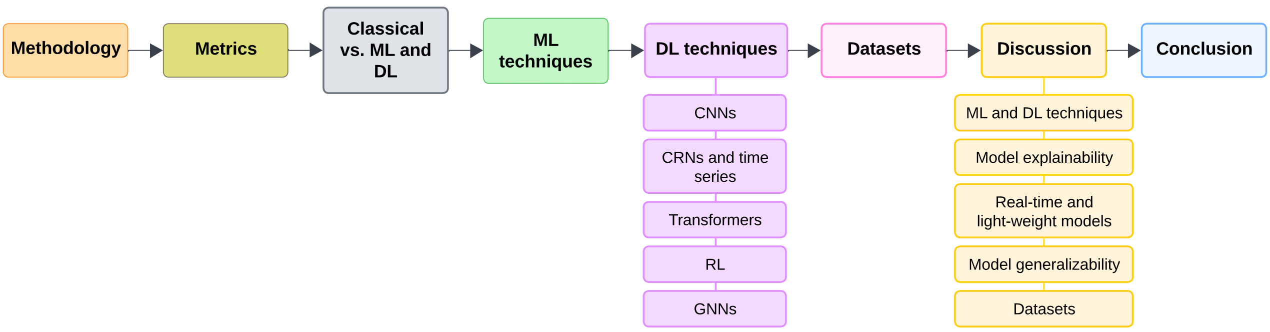

Figure 1. Diagram depicting the structure of the paper.

2. Methodology

To conduct the systematic review, the guidelines by Carrera-Rivera et al. for reviews in computer science research were followed [11].

To guide us through the entire review, we asked the following research questions "What machine learning and deep learning techniques are the most efficient in wildfire spread prediction?" and "What datasets are used for fire spread prediction?".

The keywords used to gather studies are "wildfire", "fire", "forest fire", "wildland fire", "deep learning", "machine learning", "fire spread prediction", "fire spread modeling". We used different combinations of these keywords with "OR" and "AND" operators on IEEE Xplore, Scopus, and Google Scholar to search for articles.

We did not limit the research by time. Only accessible articles from conferences and journals were included. The quality of each article was assessed based on the methodology, the results and interpretation, and the impact and contribution.

We followed that strict protocol to ensure a thorough review and the limitation of bias. The PRISMA flow diagram [12] as shown in Figure 2 presents the initial articles gathered and the final articles presented in this work.

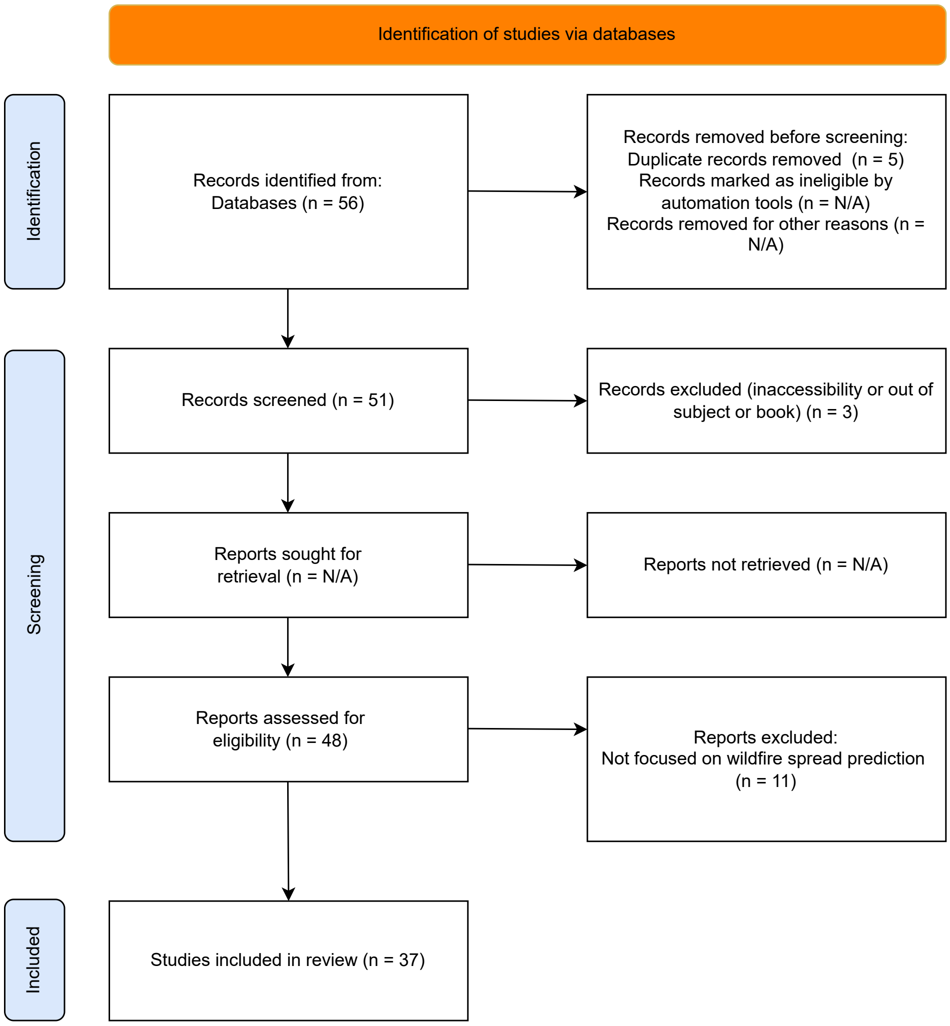

Figure 2. The PRISMA flow diagram shows the gathered studies' systematic selection process.

3. Metrics Used for Wildfire Spread Prediction Models

Metrics are crucial in wildfire spread prediction because they are critical to the performance evaluation of models, the improvement of models, the comparison of models, and the applicability of models in real-world scenarios. In wildfire spread prediction, different metrics are used depending on the task:

- Regression metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) are often used to quantify the error in the prediction of burned areas.
- Classification metrics used in wildfire spread prediction, such as accuracy, precision and recall, and F1-score, are practical when predicting binary outcomes, like the presence or absence of fire in a specific area or burned or non-burned areas.
- Spatial metrics such as Intersection over Union (IoU), also called the Jaccard index, and Sorensen–Dice Coefficient are utilized in spatial prediction models to measure the overlap between the predicted and actual burned areas and to evaluate image-based or segmentation models used in wildfire spread prediction.

The choice of metric is essential in wildfire spread prediction to efficiently assess machine learning and deep learning models. Metrics often differ from one application to another depending on the task to be performed or the dataset. Table 1 offers an overview of the metrics encountered in this literature review.

Table 1. Common metrics used in wildfire spread prediction.

Metric	Task Type	Common Use
Mean Absolute Error (MAE)	Regression	Measuring prediction error in burned area size
Root Mean Squared Error (RMSE)	Regression	Assessing the magnitude of errors, putting a focus on larger prediction errors
Mean Absolute Percentage Error (MAPE)	Regression	Comparing prediction errors across different regions or scales
Accuracy	Classification	Measuring overall correctness of fire occurrence prediction
Precision	Classification	Measuring the accuracy of positive fire occurrences, showing the proportion of correctly predicted positive instances out of all predicted positives
Recall	Classification	Measuring how well the model identifies true positive fire occurrences, indicating the proportion of actual positive fire occurrences correctly detected
F1-score	Classification	Balancing precision and recall in imbalanced data
Intersection over Union (IoU)	Spatial overlap	Evaluating the accuracy of predicted versus actual burned areas by measuring their overlap relative to the total area covered by both
Sorensen–Dice coefficient	Spatial overlap	Measuring the similarity between predicted and actual burned areas

4. Comparison of Classical Techniques to Machine Learning and Deep Learning Techniques

Machine learning and deep learning techniques offer novel alternatives to classical methods. Classical simulators like FARSITE [13] and Prometheus [14] have been the conventional methods of wildfire modeling. Those simulators rely on physics-based models that simulate fire behavior based on environmental inputs. FARSITE [13] was developed by the U.S. Forest Service and uses spatial data such as topography, fuel type, and weather conditions to simulate fire growth in a landscape. It employs the Rothermel surface fire spread model [15] to calculate the rate of fire spread based on fuel characteristics and environmental data. Even though FARSITE is highly detailed, it requires extensive data preparation and can be computationally intensive. Prometheus [14] was developed in Canada and also uses physics-based models, but integrates the Canadian Forest Fire Danger Rating System to predict fire behavior. It applies wave propagation algorithms to simulate fire spread across heterogeneous landscapes. While these traditional models are robust and have been validated through years of field use, they often require precise input data and can struggle with real-time adaptability due to their computational demands.

In contrast, ML and DL approaches offer a data-driven alternative that can overcome the limitations of traditional models. Techniques like CNNs, such as in FireCast [16], leverage satellite imagery, weather forecasts, and historical fire data to predict fire spread patterns. These models can automatically learn complex spatial-temporal patterns from large datasets without explicit programming of all environmental interactions. A significant advantage of ML and DL models is their ability to incorporate diverse data sources, like remote sensing data from satellites that provide near-real-time updates on active fires and vegetation variables. This allows those models to adapt quickly to changing conditions.

ML- and DL-based systems can outperform classical simulators under certain conditions. For instance, FireCast has demonstrated superior performance compared to FARSITE [13] in predicting fire perimeters. The MA-Net architecture [17] has been used to predict large-scale fire spread with a forecasting window of 1–5 days, which demonstrates the potential of certain DL architectures for long-term predictions. However, the effectiveness of ML and DL techniques heavily depends on the availability and quality of training data. Unlike traditional models that rely on established physical principles, ML and DL models require extensive datasets for training to ensure accurate predictions. Moreover, while ML and DL models excel in adaptability and scalability, they may lack interpretability compared to physics-based models. Understanding the underlying mechanisms driving predictions is crucial for fostering trust among fire authorities and decision-makers.

5. Machine Learning Techniques for Wildfire Spread Prediction

As wildfires become more frequent and pervasive, researchers have adopted machine learning methods to capture the variables involved more effectively.

Researchers explored several approaches for using machine learning in wildfire spread, including combining machine learning with traditional methods or other strategies for wildfire management. Zheng et al. [5] introduced a technique that integrates Extreme Machine Learning (EML) into the classical forest fire Cellular Automaton (CA) framework to simulate the spreading of forest fires. The EML was used instead of defining rules on the physical principles of forest fires in the CA framework. The combined model was validated using wildfire data from five historical fires in the west of the United States. The influence of wind (direction and speed) and topography were explicitly incorporated into the model. Fire spread was simulated in discrete time steps, with a fixed step size determined by cell size (30 m) and rate of spread calculations. The results showed an accuracy of up to 82.08%. They concluded that the approach effectively simulated the fire dynamics. To address the issue of mountain fire containment, Imran et al. [18] proposed a three-fold methodology. First, an optimization model for effective fire containment resource utilization. Second, an ensemble model based on machine learning, the heuristic approach, and principal component regression for predictive analytics of fire spread data. Last, a real-time notification of safety authorities based on the Internet of Things (IoT). They utilized a dataset comprised of mountain wildfires collected from different sources including the Hallasan Mountain dataset [19], the Kaggle Wildfire dataset [20], and the UCI dataset. They also used generated data using the SmartQFire tool for fire spread and containment simulation [21] with weather data such as temperature, humidity, wind speed, rainfall, fire-specific data such as fire spread rate, heat rate, flame speed, burned area, and fire intensity, cost of fire fighting resources per foot of mountain fire, and temporal data including the initial fire burning time and the smoldering time. The ensemble model achieved a Mean Absolute Percentage error (MAPE) of 6.42% for fire spread prediction and 9.04% for burned area prediction. Forest fire factors are too complex to be modeled using solely conventional approaches like CA. To address this, Xu et al. [22] proposed a model combining a least squares support vector machines (LSSVM) with a three-dimensional forest fire CA framework. The fire spread was simulated using the CA framework. The LSSVM was used to calculate non-linear state transition probabilities for burning. They used digital elevation map data including slope, aspect, elevation, and vegetation index extracted from Landsat8 data [23,24], paired with historical fire data in 2020 in the Lushan area of Xichang City, Liangshan Prefecture, Sichuan Province. The model obtained an overlap coefficient of 97.9%. The results show that LSSVM-CA performs well in simulating the spread of forest fires and determining the probability of forest fires. Forest Fire Spread Behavior Prediction (FFSBP) [25] is a model introduced by Sun et al. to make a quantitative prediction of forest fire spread. The model encompasses two components. On the one hand, the Forest Fire Spread Process Prediction (FFSPP) model, based on a fusion of the CA model and the Wang Zhengfei model, predicts the direction and speed of forest fire spread. Simulations used a grid-based approach with a Moore-type neighborhood for cell interactions. On the other hand, the Forest Fire Spread Results Prediction (FFSRP) model forecasts the extent of the burned area using machine learning methods, mainly GBoost, XGBoost, and LightGBM. The FFSPP model uses the "3.29 Forest Fire" incident in China, which includes firefighting records taken daily, meteorological data such as wind speed, direction, temperature, and humidity during the natural spread period before the comprehensive firefighting stage. The FFSRP uses a real fire dataset obtained from Monteshinho National Forest Park in Portugal [26,27] including spatial data, temporal information, wildfire indices, the duff moisture code, the drought code, the initial spread index, meteorological variables such as temperature, relative humidity, wind speed, rainfall, and burned area values. The relative error of the FFSPP model is 28.94%, which is smaller than those observed in the FARSITE [13] and Prometheus [14] fire behavior simulation models. The FFSRP gives a Mean Absolute Error (MAE) of 16.50.

While many studies have explored hybrid approaches that combine machine learning with traditional methods, other researchers focus exclusively on employing machine learning models, highlighting their effectiveness in predicting wildfire spread. Wood [28] proposed a data-matching machine learning algorithm to predict burned areas from wildfire incidents. Using such an algorithm provides great data mining insights. He used the Transparent Open Box (TOB) learning network algorithm to avoid the use of regression, correlation, and statistical distribution assumptions in making predictions. TOB also helps to prevent the model's use of hidden layers or complex calculations. The model is trained on a fires dataset from Portugal Montesinho natural park [26,27] with input variables including burned areas and weather data. The TOB model utilizes a two-stage prediction process. The first stage is an initial data matching using squared differences across input variables. Then, an optimization using variable weights and adjustable best match counts. Cross-validation was performed with small subsets (tuning and testing subsets of 100 records each) selected to cover the entire burned area range. Final models were evaluated using the entire dataset for consistency and to avoid overfitting. The optimum TOB model achieved a Root Mean Squared Error (RMSE) of 62.21 Ha. Furthermore, the results show that transparent optimized data-matching machine learning reveals more in wildfire spread prediction and dataset than regression-based machine learning algorithms. Khanmohammadi et al. [6] explored multiple machine learning models on grassland fires. To train the model, they collected a dataset of grassland fires in Australia composed of 224 experimental fires and 59 real-world fires combined with meteorological variables such as air temperature, relative humidity, wind speed, fuel and fire behavior metrics such as dead fuel moisture content, degree of curing, pasture type, and forward rate of spread of the fire. The study showed that linear support vector regression, exponential Gaussian process regression, boosted trees, and bilayered neural network models were the best models in each model family of tested models. These models achieve a MAE of up to 2.92 km/h and a Mean Bias Error (MBE) of up to 2.05 km/h on the collected dataset. With this paper, Khanmohammadi et al. showed that machine-learning models have great potential in fire spread prediction.

A study to predict both the spread and behavior of wildfires at a specific time or in specific regions was led by Rubí et al. [29] to address the lack of such studies for the Brazilian Federal District region, inserted in the Cerrado biome. They used a dataset of the Brazilian Federal District from the Brazilian government's open data to predict wildfire behavior using variables such as the fire point of ignition, vegetation, climatic, hydrographic, and anthropogenic factors. They proposed four machine learning approaches: artificial neural network (ANN), support vector machines (SVMs), random forest, and AdaBoost. AdaBoost gave the best performance with 92.3% accuracy on the predicted area. The workflow produced can be easily extended and adapted to other Brazilian regions (e.g., Brazilian Amazonia) and probably to different countries, depending on the construction of adequate datasets. Khanmohammadi et al. [30] conducted a novel study to predict the onset of fire propagation and type of fire behavior (surface vs. crown fire) in southern Australian semiarid shrublands. They trained multiple ML models with data from experimental fires in semiarid shrublands from two studies in southern Australia [31,32]. The datasets comprised fire sustainability and crown fire occurrence, and independent variables such as meteorological data including air temperature, relative humidity, and wind speed; fuel data such as fuel age, overstorey cover, overstorey height, litter fuel moisture, suspended fuel moisture; and near-surface fuel layer load. The support vector machine model gave the best accuracy performance with 70% and 79% correctly predicted fire spread sustainability and active crown fire propagation, respectively. Using synthetically generated datasets in the SVM model fitting process led to a 20% improvement in accuracy for fire sustainability classification and a 4% improvement for crown fire occurrence prediction. They also extracted the key predictors of fire spread sustainability, which are litter fuel moisture, wind speed at 2 m, and overstorey cover. To predict the spread of wildfires, Singh et al. [33] tested different machine learning algorithms, namely decision tree regression, XGBoost regression, and ANN. They trained the models on the Next Day Wildfire Spread dataset [34,35] that includes satellite images, weather, and geography conditions aggregated across the United States from 2012 to 2020 with elevation data, wind direction and velocity, minimum and maximum temperatures, humidity and precipitation, drought index, vegetation type and density, population density, energy release component, and previous fire mask. The decision tree regressor had a depth limited to 8, and the ANN had a four-layer deep neural network. The decision tree regression gave the best RMSE with 0.1501. Table 2 summarizes the machine learning techniques to predict wildfire spread.

Table 2. Machine learning models used in wildfire spread prediction.

Ref.	Methodology	Dataset	Results
[5]	CA and EML	Five fires in the west of the United States, namely Coal Seam Fire, Spring Creek Fire, Big Elk Fire, and Bear Fire in Colorado State, and Mustang Fire in northeastern Utah State alongside vegetation features (existing vegetation type (EVT), existing vegetation cover (EVC), and existing vegetation height (EVH)), topographic data (elevation, aspect, and slope), and meteorological data.	Accuracy = 82.08%
[18]	Ensemble model	A total of 1517 incidents of mountain wildfires collected from different sources including the Hallasan Mountain dataset [19], the Kaggle Wildfire dataset [20], UCI dataset, and generated data using the SmartQFire tool for fire spread and containment simulation [21] with weather data (temperature, humidity, wind speed, and rainfall), fire-specific data (fire spread rate, heat rate, flame speed, burned area, and fire intensity), cost of fire fighting resources per feet of mountain fire, and temporal data (initial fire burning time and smoldering time).	MAPE = 6.42%
[22]	LSSVM-CA	Environmental data (slope, aspect, elevation, and vegetation index) extracted from Landsat8 [23], digital elevation and fire data points from historical fires in the Lushan area of Xichang City, Liangshan Prefecture, Sichuan Province in 2020.	Overlap coefficient = 97%

Table 2. *Cont.*

Ref.	Methodology	Dataset	Results
[25]	FFSRP	The "3.29 Forest Fire" dataset incident in Anning, China, which occurred on 29 March 2006 including firefighting records taken daily, meteorological data (wind speed, direction, temperature, and humidity) during the natural spread period before the comprehensive firefighting stage. Montesinho National Forest Park dataset [26,27]: 517 forest fire incidents recorded between January 2000 and December 2003 including spatial data (geographic coordinates for each fires), temporal information (the month and day of occurrence), wildfire indices (Fine Fuel Moisture Code (FFMC), Duff Moisture Code (DMC), Drought Code (DC), Initial Spread Index (ISI)), meteorological variables (temperature, relative humidity, wind speed, and rainfall), and burned area values.	MAE = 16.50
[28]	TOB model	Montesinho National Forest Park dataset [26,27]: 517 forest fire incidents recorded between January 2000 and December 2003 including spatial data (geographic coordinates for each fires), temporal information (the month and day of occurrence), wildfire indices (Fine Fuel Moisture Code (FFMC), Duff Moisture Code (DMC), Drought Code (DC), Initial Spread Index (ISI)), meteorological variables (temperature, relative humidity, wind speed, and rainfall), and burned area values.	RMSE = 62.21 Ha
[6]	Several ML models	A total of 283 grassland fires in Australia composed of 224 experimental fires and 59 real-world fires, meteorological variables (air temperature, relative humidity, wind speed), fuel and fire behavior metrics (dead fuel moisture content, degree of curing, pasture type), and forward rate of spread of the fire.	MAE = 2.92 km/h
[29]	AdaBoost	Fire points and climate features from five monitoring stations and satellite data on fires that occurred over the past two decades in the Brazilian Federal District, topographic data, hydrographic data, and anthropogenic features (urbanization index, distance to rivers/roads, and Normalized Difference Vegetation Index (NDVI)).	Accuracy = 92.3%
[30]	Support Vector Machine	A total of 61 experimental fires in semiarid shrublands in southern Australia [31,32] for the training. A secondary dataset of 29 fires from operational prescribed burns, experimental fires, and wildfires from different publications in southern Australia [31] for the evaluation. The datasets comprised fire sustainability and crown fire occurrence, and independent variables such as meteorological data (air temperature, relative humidity, and wind speed), fuel data (fuel age, overstorey cover, overstorey height, litter fuel moisture, suspended fuel moisture, and near-surface fuel layer load).	Accuracy = 90% (Fire spread sustainability) Accuracy = 83% (Active crown fire propagation classifier)
[33]	Decision Tree Regression	Next Day Wildfire Spread Dataset [35] comprising remote sensing data from the contiguous United States collected between 2012 and 2020 with samples representing 64 km × 64 km with 1 km resolution and elevation data, wind direction and velocity, minimum and maximum temperatures, humidity and precipitation, drought index, vegetation type and density, population density, energy release component, and previous fire mask.	RMSE = 0.15

6. Deep Learning Techniques for Wildfire Spread Prediction

Deep learning methodologies have revolutionized wildfire spread modeling and prediction by effectively addressing the intricate spatiotemporal complexities associated with fire behavior. These advancements are enabled by leveraging diverse neural network architectures, including CNNs, CRNs, transformer models, RL learning frameworks, and GNNs. Compared to traditional and classical machine learning approaches, DL techniques are capable of handling high-dimensional datasets and extracting detailed spatial and temporal features. These DL models, trained on diverse datasets, exhibit varying strengths in predicting burned areas, fire spread rates, and temporal fire progression. Despite challenges such as computational costs and dataset limitations, they represent a transformative approach in wildfire spread prediction and become tools that can save lives, protect ecosystems, and optimize resource allocation during wildfire events.

6.1. Convolutional Neural Network Models

Researchers in fire behavior modeling have started to leverage CNN architecture as they have proven efficient at capturing spatial patterns in complex and high-dimensional data.

Computation cost is one of the concerns of physical simulators of fire. Therefore, researchers have developed low computational deep learning approaches to model fire behavior and spread. Radke et al. [16] proposed FireCast to predict wildfire spread by leveraging deep learning and Geographic Information Systems (GIS). They used a CNN architecture. The model incorporated a sliding window approach with spatial and temporal data to predict the likelihood of spread on a per-pixel basis. The predictions were compared against recorded fire growth over a series of days, and predictions were generated for the next 24 h. They trained the model on wildfire perimeters from the GeoMac database [36]. They also utilized satellite images from Landsat8 [23] as visual inputs, which were used to compute the NDVI. Further variables such as digital elevation models, and historical atmospheric data (temperature, precipitation, wind direction, and speed) were input into the model. The model was evaluated using the 2016 Beaver Creek Fire in Colorado. The model obtained an average accuracy of up to 87.7%. Moreover, FireCast was designed by the authors to require low computational resources and can identify high-risk areas of fire spread up to two weeks into the future. To model the temporal and spatial evolution of wildland fire front, Hodges et al. [37] proposed the Deep Convolutional Inverse Graphics Network (DCIGN). They generated homogeneous fire spread data based on a rate of spread from the model of Rothermel [15] and heterogeneous fire spread data using FARSITE [13] to train the model. Based on the Rothermel fire spread model [15], a total of 10,000 simulation data points were generated for randomly selected combinations of parameters such as fuel model, slope, aspect, and moisture content. These were selected from uniform distributions within specific bounds. Rasterized burn maps were created every 6 h over a 24 h period. Each pixel corresponded to 1 km^2, representing fire spread over homogeneous landscapes. Burn maps 6 h apart were used as input–output pairs for training, validation, and testing. The initial burn map (at 0 h) was excluded as it contained no fire. On the other hand, based on FARSITE [13], another fire spread simulator, 2500 simulations were performed, producing approximately 17,500 burn map pairs. These simulations were performed over a 50 km × 50 km domain with a grid resolution of 30 m, later down-sampled to match the homogeneous data resolution of 1 km^2 using randomized moisture content, wind conditions, realistic landscape, vegetation, and non-combustible regions from the LANDFIRE database [38]. The model was trained and tested to predict fire spread over 6 h intervals, but can recursively predict up to 24 h. The model achieved great results with mean precision, sensitivity, F1-score, and Chan–Vese similarity of 97%, 92%, 93%, and 93%, respectively. Furthermore, the model can predict burned areas for up to 24 h without a significant decrease in performance. DCIGN was designed to have very low computational cost. Fitzgerald et al. [39] proposed an approach using a model that trains quickly and needs fewer computational resources. They used a U-net model and attention mechanism to predict wildfire spread over the next 24 h. The U-net encoder-decoder structure, which effectively processes spatial information with fewer layers compared to deeper architectures, and the use of attention blocks to prioritize relevant spatial regions and reduce unnecessary computations, designed the model to need fewer computational resources. They used the benchmark dataset Next Day Wildfire Spread with 12 distinct features developed by Huot et al. [35] to train their model. The model achieved an F1-score of 36% using all the features. Moreover, their model trains an order of magnitude faster than prior work, using fewer computational resources. WFNet [40] is a hierarchical CNN proposed by Jiang et al. to perform a continuous time prediction of wildfire spread as Spread

Spatiotemporal Distribution Field (SSTDF). A hierarchical state-condition mechanism is proposed to customize the architecture of WFNet, which is more efficient in extracting the deep features of multimodal environmental elements than a direct encoding structure. Figure 3 shows the network architecture of WFNet with the inputs, the hierarchical state-condition mechanism and the output. To train WFNet, they generated wildfire data using FARSITE [13] and landscape data of the Californian state from LANDFIRE [38]. They also further validated the data on the real wildfire case, Burris Fire. WFNet achieved a Jaccard of 69% and a Sorensen of 81.7%. The average computation time required by the WFNet model is nearly three orders of magnitude less than that of the FARSITE model. Moreover, WFNet is robust when the input fire state is uncertain, enabling investigators to quickly backward the ignition from the fire perimeter.

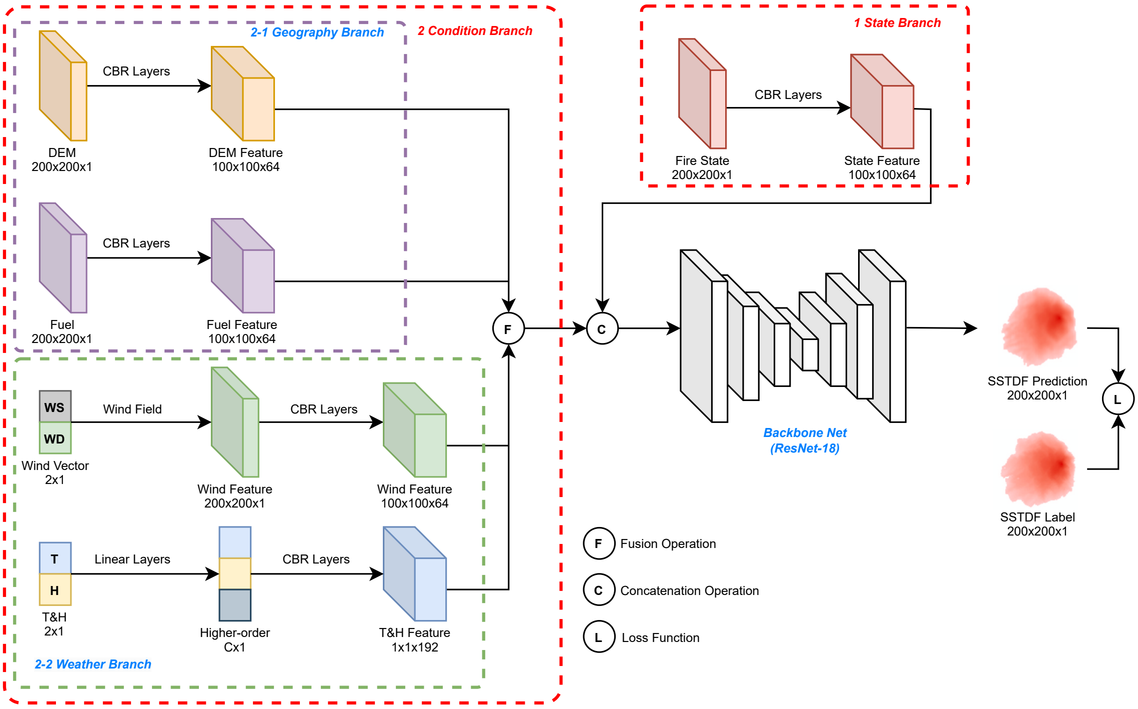

Figure 3. Overview of the WFNet network architecture in [40]. The CBR (Conv + BN + ReLU) layer consists of convolution (Conv), batch normalization (BN), and rectified linear unit (ReLU) modules. Weather branch encodes important weather parameters, such as the wind speed (WS) and wind direction (WD), temperature (T) and humidity (H).

Exploring different spatial and temporal resolutions is important in wildfire spread as it impacts the accuracy and relevance of the predictions. Bolt et al. [41] proposed a spatio-temporal neural network framework to capture complex fire spread behavior. The framework is structured with three components. The first component is an auto-encoder that encodes and decodes the fire input state. The outer component integrates the auto-encoder, spatial and forcing data, and weather data. The last component is a shallow U-net to handle the dynamics of the emulator. Simulated fires from the simulator Spark [42] were used to train and validate the framework, along with topographic data, land classification data, weather data in a time series format, such as temperature, relative humidity, wind speed and direction, and fixed parameters for each fire, such as drought factor and curing factor. All spatial data were reprojected to a consistent coordinate reference system with a spatial resolution of 30 m per pixel. The training and validation data consisted of simulated fires in the South Australian region, with a large bias towards grassland. The model achieved a Jaccard score of 76% for up to 11.5 h fire duration. The framework predictions have behavior similar to that of targeted fire simulations. The proposed approach can approximate forecasts at fine spatial and temporal resolutions. Furthermore, the data augmentation makes the proposed framework robust even with small training sets.

Leveraging CNN architecture permits the achievement of efficient and high-performing models. Khennou et al. [43] introduced FU-NetCast, a deep learning model based on the U-net model to forest fire spread over a day. FU-NetCast was designed for pixel-wise fire spread prediction. Based on initial fire perimeters and associated features, predictions were made for a 24 h time frame. They used fire locations and perimeters from the GeoMac dataset [36], providing wildfire perimeter records spaced 24 h apart, along with satellite images from Landsat8 [23], digital elevation model maps, and weather data. FU-NetCast achieved an accuracy of 92.73%. Khennou et al. further improved their model and presented FU-NetCastV2 [44] for fire spread prediction and burned area mapping. The improved model showed a 1.9% improvement over the previous one. To analyze the effect of atmospheric and environmental variables on wildfire spread, Liz-López et al. [45] introduced the Wildfire Assessment Model (WAM). The WAM employs a residual-style convolutional network architecture over atmospheric data and greenness index to compute necessary resources, the control and extinction time, and the expected burned surface area. The model was pre-trained on over 100,000 examples of unlabelled data allowing it to achieve excellent performances. The pre-trained model is then trained and evaluated on wildfire data records taken from the regions Castilla y León and Andalucía in Spain where each fire includes the coordinates of the event, burnt area in square meters, time control (minutes) and extinction (minutes), human resources (personnel), and aerial and heavy equipment resources involved in extinguishing the fire. They also utilized atmospheric data such as wind components, dew point temperature, solar and thermal radiation, total column ozone, and the greenness index. The results showed that the model achieved an accuracy of 86.1%. The pre-training allowed the model to outclass other models on wildfire spread prediction. To predict the spreading of wildfires, Marjani et al. [7] proposed a multi-kernel convolutional neural network. The multi-kernel CNN model consists of 32 layers and 33 connections. The convolutional layers utilize three different kernel sizes (3×3, 5×5, 7×7) to extract features at multiple scales. Features are processed through a series of encoder blocks with increasing numbers of filters (16 to 256) and a decoder to output burn probability maps. The model outputs a 64×64 binary fire map, where each pixel represents the likelihood of burning. They used the remote sensing dataset Next Day Wildfire Spread [35] that combines wildfires across the United States and 12 bands, including elevation, wind direction and speed, minimum and maximum temperatures, humidity, precipitation, drought index, NDVI, and energy release component. Their model achieved an accuracy of 98.6% and an F1-score of 70.97%. They claim that multi-kernel CNN can extract more high-level features and assist in learning wildfire spread patterns.

Transparency and explainability are critical in wildfire modeling to bring practical insight into wildfire management and mitigation strategies. To address the transparency of wildfire spread models, Marjani et al. [46] introduced an explainable convolutional neural network model focusing on the use of atrous spatial pyramid pooling (ASPP) mechanisms in these networks (CNN-ASPP). They used the benchmark dataset Next Day Wildfire Spread [35] to train the CNN-ASPP model. The CNN-ASPP model achieved an F1-score of 97% for a neighborhood size of 7×7. Furthermore, using the ASPP module, they found that higher Dilation Rate (DR) values, or broader patterns in the data, are appropriate to extract general patterns in wildfire spread prediction tasks. While the lower DR values, capturing more details in the data, can be used for small-size wildfire spread and have some benefits in predicting the small edges and curves of wildfires. They also used the Gradient-weighted Class Activation Mapping (Grad-CAM) algorithm to visualize feature importance across layers, which help fire management authorities to interpret which features impact fire spread. This study contributes to developing more explainable models for predicting wildfire spread, potentially offering valuable insights for wildfire management and prevention strategies.

Table 3 provides an overview of the convolutional neural network techniques used for wildfire spread prediction.

Table 3. Convolutional-neural-network-based models for wildfire spread prediction.

Ref.	Methodology	Dataset	Results
[16]	FireCast	Fire locations and perimeters from GeoMac [36], satellite images from Landsat8 [23], Normalized Difference Vegetation Index (NDVI), digital elevation models, and historical atmospheric data (temperature, precipitation, wind direction, and speed).	Accuracy = 87.70%
[37]	DCIGN	A total of 10,000 simulations generated with the Rothermel [15] fire spread simulator with random combinations of parameters (fuel model, slope, aspect, and moisture content). A total of 2500 simulations from the FARSITE [13] simulator, producing approximately 17,500 burn map pairs with randomized moisture content, wind conditions, realistic landscape, vegetation, and non-combustible regions from the LANDFIRE database [38].	F1-score = 93%
[39]	U-net with attention mechanism	Next Day Wildfire Spread dataset [35] comprising remote sensing data from the contiguous United States collected between 2012 and 2020 with samples representing 64 km × 64 km with 1 km resolution and elevation data, wind direction and velocity, minimum and maximum temperatures, humidity and precipitation, drought index, vegetation type and density, population density, energy release component, and previous fire mask.	F1-score = 36%
[40]	WFNet	Training: wildfires data generated using FARSITE [13] and landscape data of the Californian state obtained from LANDFIRE [38] Evaluation: real wildfire case Burris Fire	IoU = 69%
[41]	Spatio-temporal Fire emulator	A total of 195 simulated fires in the South Australian region generated by the Spark simulator [42] alongside land classification maps, topographic data, weather conditions, drought factor and curing factor. Grassland is the main land classification used.	IoU = 76%
[43]	FU-NetCast	A total of 120 wildfires perimeters from GeoMac [36], Landsat8 [23] images from bands 2 to 7, digital elevation model, aspect, slope, and weather data.	Accuracy = 92.73%
[44]	FU-NetCastV2	Wildfires perimeters from GeoMac [36] from 2013 to 2019, Landsat [23] images from bands 2 to 7, digital elevation model, aspect, slope, and weather data.	Accuracy = 94.63%
[45]	WAM	Pre-training with 100,000 samples of unlabelled data. In total, 597 wildfire data records taken from the regions Castilla (446) y León and Andalucía (151) where each fire includes the coordinates of the event, burnt areas in square meters, time control (minutes) and extinction (minutes), human resources, aerial and heavy equipment resources involved in extinguishing the fire, atmospheric data (wind components, dew point temperature, solar and thermal radiation, total column ozone), and the greenness index.	Accuracy = 86.10%
[7]	Multi-kernel CNN	Next Day Wildfire Spread dataset [35] comprising remote sensing data from the contiguous United States collected between 2012 and 2020 with samples representing 64 km × 64 km with 1 km resolution and elevation data, wind direction and velocity, minimum and maximum temperatures, humidity and precipitation, drought index, vegetation type and density, population density, energy release component and previous fire mask.	F1-score = 70.97%
[46]	CNN-ASPP	Next Day Wildfire Spread dataset [35] comprising remote sensing data from the contiguous United States collected between 2012 and 2020 with samples representing 64 km × 64 km with 1 km resolution and elevation data, wind direction and velocity, minimum and maximum temperatures, humidity and precipitation, drought index, vegetation type and density, population density, energy release component, and previous fire mask.	F1-score = 97%

6.2. Convolutional Recurrent Networks and Time Series Models

Several approaches to wildfire spread prediction harness the convolutional recurrent networks architecture because of its capacity to effectively capture both the spatial and temporal nature of fire behavior.

Jindal et al. [47] proposed a combined dynamic model to simulate the spread of wildfires. The first part is a long-term recurrent convolutional neural network (LRCN), used to process image sequences and predict terrain fire likelihood. The second part is a Markov Decision Process (MDP) to simulate the fire spread. They created their dataset of Google Earth screenshots of 37 forest fire incidents on the Rocky Mountain Range and the underlying regions in the United States and Canada. The screenshots were taken at six-hour intervals to create a temporal dataset that reflects the progression of fire spread. The dataset also incorporated the time (month, day), longitude and latitude, and weather data, such as wind, temperature, rain, area, and relative humidity. The LRCN model was trained using labeled data, where each pixel in the images was categorized based on its fire likelihood. The MDP used terrain fire likelihood and environmental parameters to simulate the fire spread across the grid. Initial ignition points were manually marked on the grid and the simulation considered transitions in eight cardinal and ordinal directions, constrained by environmental factors like topography and wind. In addition, the spread dynamics included a "fire aging" component to mimic the natural decay of fire intensity over time. The accuracy of fire spread predictions was evaluated using burn area ratio, which is the ratio of simulated burn area to actual burn area, and burn boundary similarity, which measures the similarity between the boundaries of the simulated and actual burn areas. Their model achieved an accuracy of 82%. Li et al. [48] designed three kinds of deep learning models based on Long Short-Term Memory (LSTM) to predict fire spread rate while exploring the interaction between fire and wind. They conducted combustion experiments to gather data at Maoershan, Harbin, Heilongjiang Province, China. The combustibles included surface fuels from coniferous forests dominated by pinus sylvestris and broad-leaved forests dominated by poplars. The fire spread prediction training data was collected with an infrared camera mounted on an unmanned aerial vehicle (UAV). Wind data are recorded with an anemometer on the same UAV. The controlled variables were slope inclination, fuel bed thickness, water content, and fuel density. In total, 13 experimental setups were created, varying these controlled parameters to simulate diverse environmental conditions. The model used fire spread rate and wind speed at the previous and current time steps as inputs and was designed to test generalization across controlled and uncontrolled conditions. FNU-LSTM gave the best results from the model tested with a RMSE of 1.065. Furthermore, the model was tested on two historical wildfires and demonstrated its efficiency on real fires. Adhikari et al. [49] proposed a hybrid deep learning model combining a CNN and a LSTM model to predict wildfire progression. They focused on wildfires in Sonoma County, California State, although the model can be adapted for other regions. The dataset comprises satellite pictures, burned area extent, vegetation indices, land cover type, temperature, wind speed and direction, relative humidity and rainfall, fire perimeters and hotspots. The CNN component was designed to extract spatial features from satellite imagery, such as vegetation patterns, terrain types, and fire hotspots. The LSTM network modeled the temporal dependencies in wildfire progression, such as the relationship between weather patterns and fire spread over time. A fusion layer is added to combine the spatial features from the CNN and the temporal features from the LSTM. The model achieves an accuracy of 85.87% and a F1-score of 92.17%. The proposed model presents high spatial accuracy and outperforms baselines, particularly in capturing the direction and intensity of fire progression under variable wind and weather conditions.

Real-time approaches are crucial to guide fire management authorities in making decisions. Marjani et al. [50] integrated the CNN and Bidirectional Long Short-Term Memory (BiLSTM) modules to develop a novel deep learning model called CNN-BiLSTM for near-real-time wildfire spread prediction. They used the Visible Infrared Imaging Radiometer Suite (VIIRS) active fires and a wide range of environmental variables, including topography, land cover, temperature, NDVI, wind information, precipitation, soil moisture, and runoff for training. The dataset focuses on fires in Laura, Queensland, Australia, from September 2015 to December 2015. The model achieves near real-time prediction by using a patch-based approach and efficient preprocessing techniques, such as resampling and normalization, to ensure computational efficiency and adaptability to evolving fire conditions. Additionally, the model predicts the next day's fire spread using a rolling window of the previous four days, enabling continuous updates and rapid integration of new data. The model gave an F1-score of 64% on the validation data. They found that soil moisture predictions and environmental variables provided the best correlation. Li et al. [51] proposed a novel dual model deep learning approach to achieve a super real-time forecast of 2-dimensional wildfire spread. The first model leverages the U-Net model to predict the burnt area up to 5 h in advance with a 5 min step. The second model utilizes the ConvLSTM model to calibrate the predicted results based on real-time updated input data. To train and evaluate this approach, they generated a numerical database of wildfire cases with the FARSITE [13] simulator. Results showed that both models performed well, with an overall agreement of over 90% between the simulations and the predictions. The real-time wildfire forecasts are faster by two to four orders of magnitude than direct simulations and take only a few seconds. This study demonstrates the potential of artificial intelligence for rapid and high-resolution forecasts of wildfire spread and the innovative contribution of using two models that work together to be utilized at various stages of wildfire management.

Some studies have conducted comparative analyses of various models to evaluate their performance and accuracy. Perumal et al. [52] compared the Gated Recurrent Unit (GRU) with the Long Short-Term Memory for fire spread modeling. They used data points from South Africa extracted from the VIIRS instrument. The data included latitude and longitude, time and date, fire radiative power and elevation. All continuous variable in the dataset were normalized for training. They found that the GRU model performed better for long-time series than the LSTM model. Khalaf et al. [53] conducted a performance comparison of famous wildfire spread algorithms, namely ConvLSTM, FlamMap, and CA in the Golestan National Park (GNP), Iran. The dataset used consisted of spatial and temporal wildfire data for Golestan National Park (GNP) in northeast Iran, focusing on three large historical wildfires occurring between 2010 and 2018. The input variables included topographic data such as elevation, slope, and aspect, weather conditions such as wind speed, direction, temperature, humidity, vegetation characteristics, and fuel models. The dataset encompassed 325 simulated fires using BehavePlus and FlamMap for ConvLSTM training, reflecting different wind speed scenarios, direction, and fuel moisture. The ConvLSTM algorithm achieved the highest Sorensen coefficient values across all three fires, ranging from 78% to 82%, while FlamMap tended to underestimate and the CA tended to overestimate. Regarding the rate of spread, the CA algorithm performed better than the other algorithms. This study is consistent with earlier research, demonstrating that ConvLSTM effectively predicts burned areas during wildfires.

Time resolution is a critical variable at play in wildfire spread prediction. Marjani et al. [54] introduced FirePred, a hybrid multi-temporal convolutional neural network to leverage varying temporal resolution. Figure 4 shows an overview of this multi-temporal architecture. They trained their model on British Columbia wildfire events. In addition, burned areas were mapped using the Moderate Resolution Imaging Spectroradiometer (MODIS) [55]. They also incorporated environmental variables, including slope, aspect, digital elevation model (DEM), land cover, temperature, precipitation, wind speed and direction, and population density. The data were grouped into three blocks: the hourly block, which included wind data averaged over 6 h; the daily block, which included temperature, precipitation, and wildfire masks; and the constant block, which included DEM, slope, land cover, and population density. They further assessed their model using a dataset encompassing 10 wildfires in Alaska and a wildfire occurrence in Nova Scotia. FirePred reached an F1-score of 94%. The results indicated that regional parameters can affect the model's performance. Moreover, introducing an uncertainty protocol revealed that the perimeters of the wildfires are the primary contributors to the uncertainty.

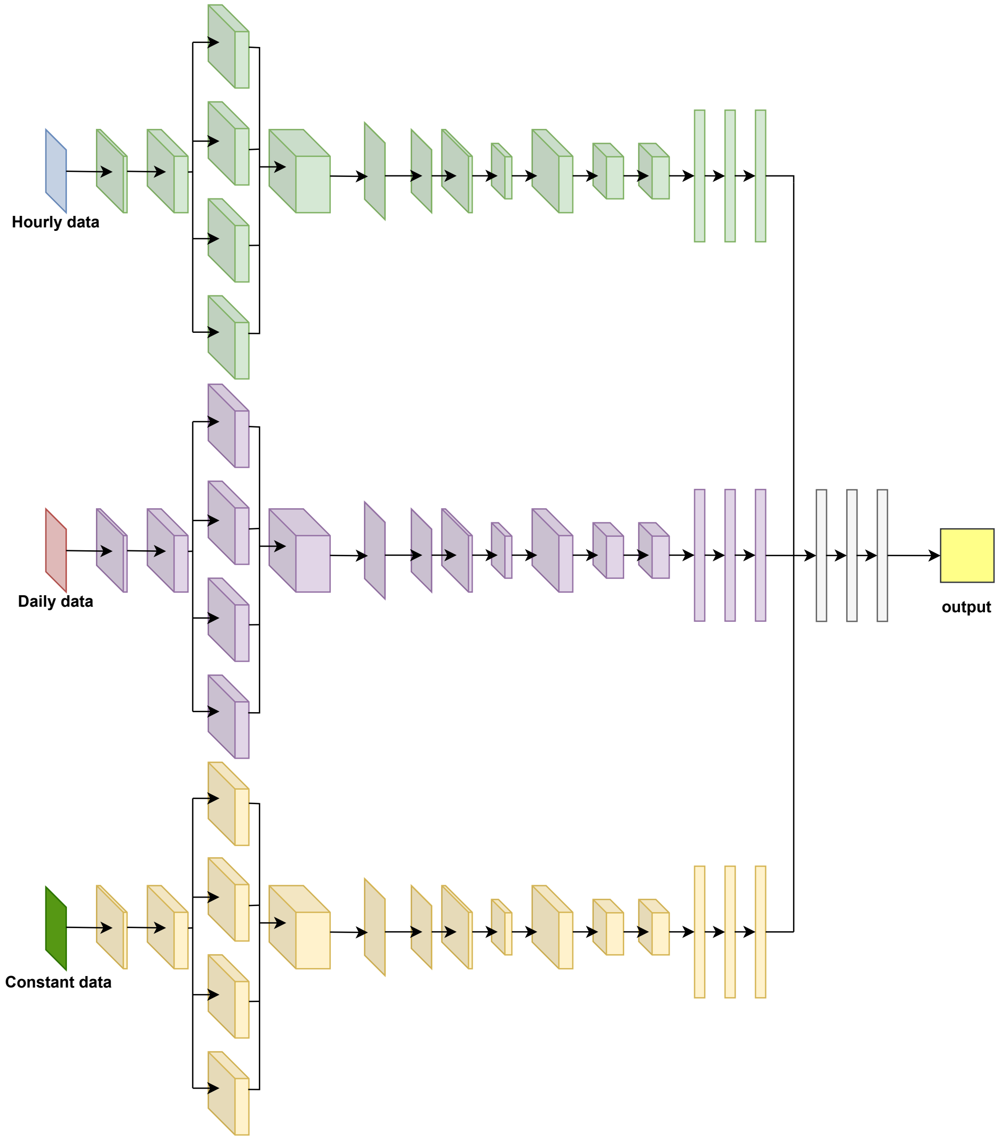

Figure 4. Overview of the multi-temporal convolutional neural network architecture in [54].

Another approach to modeling the time-resolved dynamics of wildfires is evaluated by Burge et al. [56]. They proposed an autoregressive process in which a convolutional recurrent deep learning model makes predictions that propagate a wildfire over 15 min increments. The data they used included 30,000 simulations across three distinct datasets of increasing complexity. The first dataset is a single fuel dataset that contains simulations using a uniform fuel model across the entire landscape, where the terrain was planar with constant slope and aspect. The second dataset is a multiple fuel dataset that contains simulations with variations in fuel models, randomly selected for each simulation from predefined types. The last dataset is a California dataset based on real-world landscapes, with data obtained from the LANDFIRE program [38]. Random fields were sampled from California's geographical extent, avoiding non-burnable areas like water bodies. The dataset was parameterized using various attributes, such as fuel type, wind direction, slope, and moisture content, with ranges provided in the study. They utilized dynamic inputs such as vegetation, fire fronts, and fire scars, and static factors like wind speed and direction, fuel model, and terrain slope. Each simulation covered a domain discretized into a 128 × 128 grid with cell sizes of 30 m. The models were evaluated on their ability to predict wildfire spread over time using an autoregressive approach, where predictions for one time step were used as inputs for the next. Outputs included the fraction of each grid cell's burned area. The model generates stable results and realistic propagation dynamics, achieving a Jaccard score between 89% and 94% when predicting the resulting fire scar even after 100 autoregressive predictions representing more than 24 h of simulated fire spread.

Exploring strategies to use simulated data can significantly enhance the performance of deep learning models in fire propagation prediction. To capture and interpret the dynamics of wildfire spread, Masrur et al. [8] proposed two unique attention-based spatiotemporal models using ConvLSTM networks. The first model incorporates a pairwise self-attention, while the other integrates a patchwise self-attention. These networks are designed to learn and capture a range of local to global, short and long-range spatiotemporal correlations leveraging the self-attention mechanisms. The authors focus on evaluating the models' ability to predict wildfire spread patterns over 10 future time steps using 10 prior time steps, and capturing both local interactions (fire front) and long-range effects (spotting fires). The models were tested on two datasets: a high-resolution dataset simulated using a percolation model [57], and actual wildfire events observed in California [58]. The simulated dataset represents a 110 × 110 grid corresponding to forest patches experiencing active wildfires. The variables used include the locations of unburned vegetation, burned tree vegetation, and vegetation burned prior to the time step, horizontal and vertical wind velocity components, elevation, and moisture content. The data samples are systematically generated to emulate realistic wildfire behaviors, exploring the influence of various biophysical factors. The California wildfire dataset includes vegetation data, wind components, and elevation data. The patchwise prediction gives the best results with the historical wildfire dataset with an F1-score of 96%. The study suggests there is significant potential for attention mechanisms to capture the spatio-temporal behavior of wildfire spread, with model transferability, that can benefit wildfire management operations. Table 4 outlines the CRNs and time series models applied in wildfire spread prediction.

Table 4. Convolutional recurrent networks and time series models for wildfire spread prediction.

Ref.	Methodology	Dataset	Results
[47]	LRCN and MDP	A total of 37 forest fire incidents screenshots on the Rocky Mountain Range, time (month, day), longitude and latitude, and weather data (wind, temperature, rain, area, and relative humidity)	Accuracy = 82%
[48]	FNU-LSTM	Infrared images of fire data and wind data collected on a unmounted aerial vehicle during burning experiences	RMSE = 1.06
[49]	CNN-LSTM	Satellite data of fires in Sonoma County, California State with burned area extent, vegetation indices, land cover type, temperature, wind speed and direction, relative humidity and rainfall, fire perimeters and hotspots.	F1-score = 92.17%
[50]	CNN-BiLSTM	Visible Infrared Imaging Radiometer Suite (VIIRS) active fires and environmental variables, including topography, land cover, temperature, NDVI, wind information, precipitation, soil moisture, and runoff in Laura, Queensland, Australia from September 2015 to December 2015	F1-score = 64%
[51]	U-Net and ConvLSTM	Generated numerical wildfire database consisting of 210 cases (12,600 samples) with the FARSITE simulator [13] in 5 m spatial resolution and 5 min temporal resolution	IoU > 80%
[52]	GRU LSTM	Data points of South Africa extracted from the Visible Infrared Imaging Radiometer Suite (VIIRS) for the years 2012–2014 including latitude and longitude, time and date, fire radiative power and elevation.	Accuracy = 38% Accuracy = 36%
[53]	ConvLSTM	A total of 325 fire simulations using FlamMap and BehavePlus for training. Tested on historical fires in the Golestan National Park, Iran	Accuracy = 89.67%

Table 4. *Cont.*

Ref.	Methodology	Dataset	Results
[54]	FirePred	Training: 177 wildfire events between 2002 and 2018 in British Columbia, Canada, burned areas, environmental variables (slope, aspect, DEM, land cover, temperature, precipitation, wind speed and direction, and population density). Evaluation: ten wildfires in Alaska between 2016 and 2019 and a wildfire occurrence in Nova Scotia during 2023.	F1-score = 94%
[56]	EDP-convLSTM	Wildfire simulations split into three subsets: the single fuel dataset, using a uniform fuel model on planar terrain with constant wind and slope; the multiple fuel dataset, featuring varying fuel models across simulations to test generalization; the California dataset, based on real-world landscapes with diverse topography and vegetation from the LANDFIRE database [38]. Each dataset captured different variables: vegetation burn fractions (unburnt, burned fire front, scar), wind components, moisture levels, topographic features (slope, elevation), and canopy characteristics (height, density, crown ratio).	IoU = 89%
[8]	convLSTM with self-attention	Forest patches simulated dataset with the locations of unburned vegetation, burned tree vegetation, vegetation burned prior to the time step, horizontal and vertical wind velocity components, elevation, and moisture content. California wildfire spread dataset derived from the VIIRS satellite observations [58] including vegetation data, wind components, and elevation data.	F1-score = 96%

6.3. Transformer Models

As transformers can handle long-range dependencies, they have been increasingly used in modeling environmental phenomena, including wildfire behavior.

Qayyum et al. [59] introduced a deep learning model based on a transformer to predict fire spread. They employed SHapley Additive exPlanations (SHAP) to address the interpretability of the deep learning model, i.e., to explain the connection between the input variables and the model outputs across different parameters. The SHAP framework transforms the deep learning model into an interpretable tool by quantifying the contribution of each input feature to the model's predictions, clarifying the driving factors behind wildfire spread rates. A dataset of grassfires in Australia was used to train and test the model. The records of fire spread come from various sources, including both experimental and real wildfires, and comprise input features such as air temperature, relative humidity, wind speed, moisture content in dead fuels, degree of vegetation curing, classification of pasture, and fire type. The target variable is the rate of spread of fire in km/h. The model showed effective accuracy and reliability. Furthermore, the use of SHAP significantly contributed to the interpretability of the model, advancing better decisions in wildfire management and security. Wind speed emerged as the most critical variable influencing the rate of fire spread, as highlighted by SHAP value analysis. Other significant variables included vegetation curing and moisture content. Li et al. [60] proposed a novel deep learning technique, the Attention Swin U-net with Focal Modulation (ASUFM), to predict wildfire spread in North America. The ASUFM model incorporates spatial attention and focal modulation into the transformer model Swin U-net. Figure 5 depicts an overview of the architecture. To train and validate the model, they used the Next Day Wildfire Spread benchmark [35] that incorporates remote sensing data. In addition, they extended the dataset to encompass wildfire data across North America from 2012 to 2023. Each sample in the dataset consists of 12 layers of 64 × 64 pixel images that include environmental and meteorological features, including the previous day's fire mask, elevation, wind direction and speed, minimum and maximum temperatures, humidity, precipitation, drought index, vegetation, population density, and energy release component. One layer of the dataset represents the target, which is the fire mask for the next day. On the original dataset, the model achieved a Precision-Recall Area Under the Curve (PR-AUC) of 37%. Furthermore, the model generalizability and balanced performance were verified with the extended dataset with an improved PR-AUC of 39%.

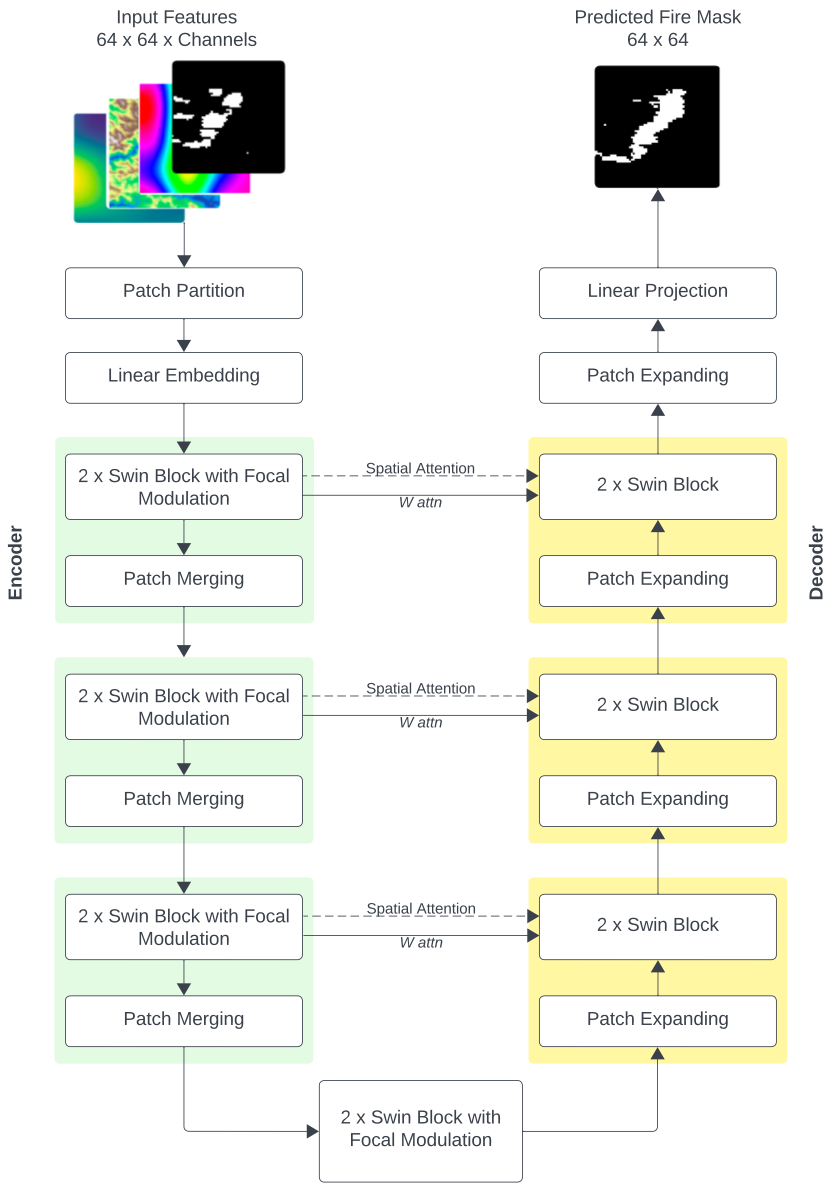

Figure 5. Overview of the ASUFM architecture in [60].

In their paper, Chen et al. [61] proposed a model to predict forest fires by leveraging spatio-temporal data. In their model AutoST-Net, they used an encoder-decoder architecture that combines a three-dimensional convolutional neural network (3DCNN) with a transformer. The model further integrates an innovative attention mechanism to increase predictive precision. They developed a dataset of southwestern forest regions of China that can be easily adapted from remote sensing data for other areas. The dataset combines seven fires with 10 influential factors, including forest fire status, weather conditions, terrain features, and vegetation status based on Google Earth Engine (GEE) and Himawari-8 satellite. The seven forest fire events contributing to the dataset comprise 2000 samples with 10 layers: fire mask, NDVI, elevation, terrain height, precipitation, u-wind and v-wind components, humidity and soil moisture, and drought index. The model performed 82.98% on the Mean Intersection over Union (MIoU) metric and 80.50% on the F1-score.

Shadrin et al. [17] developed a model based on a Multi-Attention Network (MA-Net) to predict fire spread on a large scale ranging from 1 to 5 days. Positional attention blocks and multi-scale attention blocks were included to capture spatial relationships and dependencies. The dataset comprises fires in the northern Russian regions between 2021 and 2022. All the fires lasted between 1 day and 3 months. They extracted earth remote sensing data to compose the dataset. They used it with static features such as land cover maps, elevation, aspect, slope maps, population density, and dynamic features such as weather data like wind speed and direction, temperature, precipitation for the days of fire prediction, vegetation indices, and evapotranspiration data. Each fire instance contains ignition points and spatial feature maps for prediction days (1–5 days). The model reached an F1-score of 68% depending on the day of prediction (from 1 to 5 days). According to their study, the most significant features are the wind direction and land cover parameters.

Table 5 summarizes the transformer models employed in wildfire spread prediction.

Table 5. Transformer models for wildfire spread prediction.

Ref.	Methodology	Dataset	Results
[59]	Transformer with SHAP	A total of 283 data recordings of experimental and historical grassfires in Australia, including variables such as air temperature, relative humidity, wind speed, moisture content in dead fuels, degree of vegetation curing, classification of pasture, and fire type.	MAE = 1.60
[60]	ASUFM	Next Day Wildfire Spread [35] extended to North America from 2012 to 2023 comprising remote sensing data from the contiguous United States collected between 2012 and 2020 with samples representing 64 km × 64 km with 1 km resolution and elevation data, wind direction and velocity, minimum and maximum temperatures, humidity and precipitation, drought index, vegetation type and density, population density, energy release component, and previous fire mask.	PR-AUC = 39%
[61]	AutoST-Net	Remote sensing data of southwestern forest regions of China comprising of seven fires and 10 influential factors, including forest fire status, weather conditions, terrain features, and vegetation status based on Google Earth Engine (GEE) and Himawari-8 satellite.	F1-score = 80.50%
[17]	Architecture based on MA-Net	Remote sensing data of 941 fires in northern Russia between 2021 and 2022 with land features (land cover map, elevation, aspect, slope maps), weather forecast data (wind speed and direction, temperature, precipitation), population density, vegetation indices, and evapotranspiration data. The fires lasted between 1 day and 3 months.	F1-score = [64–68%] depending on the day of prediction (from 1 to 5 days)

6.4. Reinforcement Learning Models

Deep reinforcement learning models' adaptability to dynamic environments makes them well-suited for the evolving nature of fire spread. Therefore, some researchers have explored techniques that leverage reinforcement learning architecture.

Subramanian and Crowley [62] introduced a combination of two deep reinforcement learning models on an online simulator of a wildfire, the Monte Carlo Tree Search (MCTS) and the Asynchronous Advantage Actor-Critic (A3C). Each wildfire was modeled as a spatially spreading Markov Decision Process (MDP), where the fire spread was predicted by maximizing a reward function based on matching observed fire spread. They trained the combined model using simulated wildfires under varying environmental conditions from the Nova online simulator [63]. The dataset also included the spatial location (x,y), temperature, land cover type, wind speed and direction, relative humidity, rainfall, fire intensity, and time since fire initiation. The validation was conducted on two massive wildfire events in Northern Alberta, Canada, and the historical Saskatchewan fires. They implemented several experiments. Experiments A and B focused on Alberta fires to predict intermediate fire spread (Experiment A) and forward prediction for 16-day intervals (Experiment B). In experiments C–F, transfer learning was applied by training on Richardson fire data and testing on the Fort McMurray fire, which occurred 5 years later in a similar region. In experiment G, they used simulated fires from the Nova simulator to test model scalability and generalization. Experiments H and I utilized historical Saskatchewan data for long-term testing: experiment H predicted fire spread from 1993 to 2002, and experiment I extended predictions to 2003–2008. The accuracy of fire spread prediction was assessed using ground truth satellite images. The burn probabilities and fire perimeters were compared with ground truth for simulations. They obtained an average accuracy of 92.4%. The MCTS-A3C model outperformed baseline algorithms in most experiments, especially in generalization tasks across different regions and times.

In another study, Subramanian et al. [64] proposed using reinforcement learning to model forest fire spread dynamics from satellite images. They tried different models. The problem was modeled as a MDP, with wildfire spread treated as an agent navigating the landscape. The study compared five reinforcement learning algorithms, namely Value Iteration, Policy Iteration, Q-Learning, MCTS, and A3C. They trained the models on wildfire events in Northern Alberta, Canada, namely the Fort McMurray fire of 2016 and the Richardson fire of 2011. The dataset consisted of visual and thermal satellite imagery, which included temperature, wind speed and direction, rainfall, relative humidity, land cover type. The dataset had a temporal resolution of 16 days. The intermediate prediction experiment (Experiment A) used data from previous and subsequent states to estimate the fire spread at an intermediate time step. In the forward prediction experiment (Experiment B), the models predicted the wildfire spread for the next 16 days based on the current state. Transfer learning experiments (Experiments C–F) tested the models' ability to apply policies learned from the Richardson fire to forecast the progression of the Fort McMurray fire over multiple time steps. They discovered that the A3C model is better at predicting spread dynamics at intermediate time steps with an average accuracy of 87.3%. The MCTS performs better while predicting the future spread with an average accuracy of 60.2%.

Table 6 summarizes the reinforcement learning models employed in wildfire spread prediction.

Table 6. Reinforcement learning models for wildfire spread prediction.

Ref.	Methodology	Dataset	Results
[62]	MCTS-A3C	Simulated and real wildfire datasets, including satellite imagery from major Alberta wildfires (Fort McMurray and Richardson fires) and historical data from Saskatchewan (1981–2008), incorporating spatial and environmental features such as location, temperature, land cover type, wind speed and direction, relative humidity, rainfall, fire intensity, and time since fire initiation.	Accuracy = 92.40%
[64]	A3C	Satellite imagery from Landsat [65,66] on the Richardson Fire (2011) and the Fort McMurray Fire (2016) with variables such as temperature, wind speed and direction, rainfall, relative humidity, and land cover type.	Accuracy = 87.30%

6.5. Graph Neural Networks

Graph neural networks are able to capture complex spatial relationships and handle irregular data structures.

As models for wildfire spread have difficulties in expressing local spread details, Jiang et al. [67] proposed a novel approach that combines an irregular graph network (IGN), a generation algorithm to characterize the wildland landscape with a variable scale, and a deep learning-based spread model. This innovative approach is superior in describing the spatio-temporal characteristics of wildfires with an explicit spread route. This is crucial for emergency management agencies to make rescue plans and avoid entering potentially high-risk areas. They used generated wildfire datasets with FARSITE [13]. A real wildfire in Getty, California State was used for the evaluation. These datasets included spatial features such as geographic coordinates, elevation, fuel type, and ignition time for graph nodes, as well as edge-specific features like length, slope, and azimuth angle. Environmental variables, including wind speed and direction, temperature, and humidity, were also incorporated to capture dynamic wildfire conditions. Target features for prediction included spread time, flame length, and fire intensity, enabling detailed modeling of wildfire behavior within the IGN model. The deep learning model, Wildfire Deep Neural Network (WFDNN), was also implemented to predict the targeted features. The combined model showed competitive simulation refinement and computational efficiency with a Jaccard coefficient of 58.7%, a Sorensen metric of 74%, and an overall accuracy of 80%.

Rösch et al. [68] introduced a data-driven deep learning approach to model wildfire spread in Europe based on a spatiotemporal graph neural network (STGNN). They developed a country-scale model based on fires in Portugal and a continental model with wildfires from the entire Mediterranean region. They constructed a dataset of European wildfires from 2016 to 2022 using the burned area perimeters [69], weather data, active fire, fuel type, and topographic data. The model performances were insufficient due to inadequate reference data quality with a weighted macro-mean IoU of 37% for the Portugal model and 36% for the continental model. However, the continental model successfully learned the typical patterns of wildfire spread with comparable performance across different fire-prone Mediterranean countries, suggesting enhanced transferability. Table 7 provides an overview of graph neural network models utilized in wildfire spread prediction.

Table 7. Graph neural networks for wildfire spread prediction.

Ref.	Methodology	Dataset	Results
[67]	IGN and WFDNN	A total of 700 wildfires generated with the FARSITE model [13] combined with landscape data from LANDFIRE [38], spatial features (geographic coordinates, elevation, fuel type, and ignition time for graph nodes), edge-specific features (length, slope, and azimuth angle), and environmental variables (wind speed and direction, temperature, and humidity).	IoU = 58.70%
[68]	STGNN Portugal STGNN continental	Dataset of European wildfires from 2016 to 2022 with burned area perimeters [69], historic weather data, fire weather index, active fire data, fuel type, land cover, digital elevation model.	IoU = 37% IoU = 36%

7. Datasets Used for Wildfire Spread Prediction

Data availability and quality could be a limiting factor for wildfire spread models [68], which highlights the importance of high-quality data in the field of fire spread prediction. Table 8 illustrates commonly used datasets for this task. Models usually involve a combination of multimodal data to achieve good performance and build efficient fire spread prediction techniques. Therefore, most datasets and data collections listed below include weather, topography, environmental, anthropogenic data, historical fires, and satellite images:

- The Montesinho natural park dataset [26,27] gathers 517 fire occurrences from the Montesinho natural park in Portugal from January 2000 to December 2003. Several features were recorded at a daily basis during a forest fire, including the time, date, spatial location within a 9 × 9 grid, the type of vegetation involved, the six components of the forest Fire Weather Index system (Fine Fuel Moisture Code (FFMC), Duff Moisture Code (DMC), Drought Code (DC), Initial Spread Index (ISI), Buildup Index (BUI) and Fire Weather Index (FWI)), and the total burned area. In addition, several weather observations (e.g., wind) were recorded within a 30 min period.
- The CAL FIRE [70] is a fire perimeters database including two layers: historical fire perimeters and prescription treatments using fire in the state of California provided by the California Departement of Forestry and Fire Protection. The fire perimeters database includes two layers—historical fire perimeters (firep) and prescription treatments using fire (rxburn)

- The historic GeoMac Perimeters [36] provided wildfire mapping data for the United States and proposed current fire locations and perimeters in the 48 states and Alaska in the USA.
- The WildfireDB [71,72] dataset regroups datapoints of daily fire occurrences from 2012 to 2018 in the continental USA. The dataset includes the following features: canopy base density, canopy base height, canopy cover, canopy height, existing vegetation cover, existing vegetation height, existing vegetation type from years 2012, 2014, and 2016, elevation and slope from year 2016, weather data (the average, minimum and maximum temperature, total precipitation, average atmospheric pressure, and relative wind speed between the two cells in consideration).
- The Mesogeos dataset [73,74] is a datacube with longitude, latitude, and time as dimensions. The dataset includes meteorology, vegetation, land cover, and human activity data alongside historical burned areas, ignitions, and burned area sizes as separate variables. The dataset covers a wide area of the Mediterranean region from 2006 to 2022, and values are presented in a 1 km × 1 km × daily resolution.
- The MCD14DL [75] gathers thermal anomalies and active fire locations products from the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor. Thermal anomalies or active fire represent the center point of a 1 km square pixel, which contains at least one fire or a thermal anomaly (such as a fire or heat source) within the area represented by that pixel. The dataset provides near real-time data with minimal processing as the data are available quickly after the satellite.
- The MCD14ML [76] provides such as the MCD14DL [75] thermal anomalies and active fire locations from the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor. While the MCD14DL [75] provides near real-time data with minimal processing, the MCD14ML [76] undergoes more rigorous processing and quality checks, resulting in higher accuracy and reliability but is typically available with a lag of about two months due to the additional processing.
- The Himawari Wildfire Product [77,78] is a satellite-based tool designed to monitor and detect wildfires and fire radiative power (FRP) in real time. The data are from the Himawari series of geostationary weather satellites operated by the Japan Meteorological Agency. The product provides frequent updates, making it suited for timely detection and monitoring of wildfire activity.
- The fire scars in Alaska and Canada [79] dataset presents wildfire progression estimations represented by date of burning (DoB) within fire scars across Alaska and Canada from 2001 to 2009. Within each burn scar, the DoB data are represented as polygons and map the daily progression of a fire.
- The Next Day Wildfire Spread [34,35] dataset combines 2D remote-sensing data across the United States with historical wildfire data and 11 observational variables at a daily temporal resolution, including elevation, wind direction, wind speed, minimum and maximum temperature, humidity, precipitation, drought index, vegetation, population density, and energy release component. The data are presented at 1 km spatial resolution.
- The FEDS [58] provides historic fires in California from 2012 to 2020 at a 375 m spatial resolution and a half-day temporal resolution. The dataset contains 35,337 active fire objects, including 735 large fires with a final size greater than 4 km^2 and 12,801 records of 12 h growth increments.
- The Landsat OLI 8 and 9 [23,24] product offers high-resolution fire and thermal anomaly data with a 30 m spatial resolution. It covers the United States area, southern Canada, and northern Mexico. The system can detect fires both during the day and at night, with improved nighttime performance.
- The Landsat C2 level-3 Burned Area [65,66] identifies burned areas in high-resolution across various ecosystems, such as forests, shrublands, and grasslands in the conterminous United-States from 1984 to the present.

- The WildfireSpreadTS [80,81] dataset introduces a multi-temporal, multimodal remote-sensing dataset of fire events in the United States at a high resolution of 375 m. The dataset contains 13,607 images across 607 fire events in the United States from January 2018 to October 2021 at a temporal resolution of one day. Furthermore, the dataset includes 23 multimodal input channels related to fuel, topography, and weather conditions.
- The Extended Next Day Wildfire Spread [60] dataset is an extension of the Next Day Wildfire Spread [34,35] dataset. The Next Day Wildfire Spread dataset contains 18,454 samples of 12 layers of 64 × 64 remote sensing images as input, including previous day fire mask and one layer of the target next day fire mask. This dataset has expanded the original data, reaching 51,388 samples, by extracting fires from 2012 to 2023 in North America.
- The Canadian Wildfire Spread dataset [82,83] is a comprehensive dataset that maps the progression of large wildfires (larger than 1000 ha) across Canada from 2002 to 2021. It provides interpolated progressions for each fire, representing the day of burning for every pixel alongside 50 environmental covariates such as daily weather conditions, topography, and forest fuel characteristics.

Table 8. Computer vision datasets for fire spread prediction.

Ref.	Data Label	Description	Spatial Resolution	Temporal Resolution
[26,27]	Forest fires within the Montesinho park	A total of 517 fires from 2000 to 2003 within the Montesinho natural park, including weekday, month, coordinates, burnt area, rain, temperature, humidity, wind, vegetation, and fuel data	NS	1 day
[70]	CAL FIRE	Historical wildland and prescribed fire perimeters from 1878 to 2023 in the state of California	NS	NS
[36]	Historic GeoMac Perimeters	Online maps of fire locations and perimeters from 2000 to 2020 in 48 states of the USA and Alaska	NS	NS
[71,72]	WildfireDB	Discretized spatial and temporal dataset of historical wildfire occurrences from 2012 to 2017 in the continental United States with vegetation, topography, and weather data	375 m	1 day
[73,74]	Mesogeos	Large-scale multi-purpose dataset in a datacube structure for wildfire modeling in the Mediterranean encompassing 27 variables related to meteorology, vegetation, land cover, human activity, historical records of wildfire ignitions, and burned areas from 2006 to 2022	1 km	1 day
[75]	MCD14DL	Near real-time representation of active fires and other thermal anomalies from November 2000 to present	1 km	1 day
[76]	MCD14ML	Daily representation of active fires and other thermal anomalies from 2001 to present	1 km	1 day
[77,78]	Himawari Wildfire Product	Location and the fire radiative power (FRP) of hot spots retrieved from the IR imageries obtained with the Himawari-8 satellite since 2016 to present	2 km	10 min
[79]	Fire scars in Alaska and Canada	Estimation of wildfire progression denoted by the date of burning (DoB) within fire scars across Alaska and Canada from 2001 to 2019.	1 km	1 day
[34,35]	Next Day Wildfire Spread	A total of 18,455 two-dimensional remote-sensing fire entries from 2012 to 2020 with topography, vegetation, weather, drought index, and population density data across the United States.	1 km	1 day

Table 8. *Cont.*

Ref.	Data Label	Description	Spatial Resolution	Temporal Resolution
[58]	FEDS	A total of 35,337 active fire objects in California over the 2012–2020 period from the VIIRS instrument	375 m	half-day
[23,24]	Landsat OLI (8 and 9)	Active fire detections and thermal anomalies data of the contiguous United States area, southern Canada, and northern Mexico from 2022 to the present	30 m	16 days
[65,66]	Landsat C2 Level-3 BA	Burned areas across all ecosystems in the conterminous United-States from March 1984 to the present containing two raster layers that represent burn classification and burn probability	30 m	16 h
[80,81]	WildfireSpreadTS	A total of 13,607 images across 607 fire events in the United States from January 2018 to October 2021 with detected active fires and variables related to fuel, topography and weather conditions	375 m	1 day
[60]	Extended Next Day Wildfire Spread	Extended version of the Next Day Wildfire Spread dataset [34,35] to 2012–2023	1 km	1 day
[82,83]	Canadian Wildfire Spread dataset	Progression maps of large fires in Canada from 2002 to 2021 with environmental variables including daily weather metrics, topography, and fuel data.	180 m	1 day

NS refers to not specified.

Some datasets are used as benchmarks across different studies. Comparing models using the same datasets highlights which methodologies are more effective under similar conditions. Table 9 presents a summary of the model using those benchmarks.

Table 9. Comparison of models across benchmark datasets

Dataset	Targets and Time Resolution	Models	Performances
Forest fires within the Montesinho park [26,27]	The target of the models using this dataset is the total burned area resulting from forest fires. The time resolution is not explicitly fixed to a time frame; it is event-based and focused on the cumulative total burned area for each specific wildfire event recorded in the dataset.	FFSRP [25]: A combination of machine learning techniques like GBoost, XGBoost, and LightGBM with a Cellular Automata-based model	MAE = 16.50
		TOB [28]: Transparent data-matching machine learning approach without hidden layers or regression assumptions	RMSE = 62.21 Ha
Next Day Wildfire Spread [34,35]	The models' target for this dataset is the fire mask at time t + 1 one day after the previous fire mask at time t.	Decision tree regression [33]: tree-based structure technique	RMSE = 0.15
		U-Net with Attention Mechanism [39]: encoder-decoder structure enhanced with attention blocks	F1-score = 36%
		Multi-kernel CNN [7]: convolutional layers with multiple kernel sizes for multi-scale feature extraction	F1-score = 70.97%
		CNN-ASPP [46]: Atrous Spatial Pyramid Pooling combined with convolutional layers to capture multi-scale contextual features	F1-score = 97%
		ASUFM [60]: Swin transformer-based blocks with focal modulation and spatial attention mechanisms to enhance feature extraction and context representation	PR-AUC = 39%

Table 9. *Cont.*

Dataset	Target and Time Resolution	Models	Performances
FEDS [58]	The models' prediction target for this dataset is the burn probability for each pixel in the wildfire area for the next day.	CNN-BiLSTM [50]: a combination of a CNN for spatial feature extraction with a bidirectional LSTM network to model temporal dependencies	F1-score = 64%
		ConvLSTM with Self-Attention [8]: convLSTM layers for spatiotemporal feature learning with pairwise and patchwise self-attention mechanisms	F1-score = 96%

8. Discussion

Wildfires have been a severe hazard in recent years and have become increasingly recurrent because of climatic change. The introduction of machine learning and deep learning to model and predict the spread of wildfires has brought unprecedented insights into wildfire mitigation strategies. However, some challenges and future directions remain to be explored in this field.

8.1. Machine Learning and Deep Learning Techniques Used to Predict Wildfire Spread

Traditional techniques like mathematical models and physical simulators have been harnessed to capture the complex behavior of fire. With the evolution of computational power and machine learning techniques, researchers have combined traditional methods with machine learning architectures [5,18,22,25]. Other studies focus on testing machine learning models on benchmark datasets to show the potential of those models in fire dynamics modeling. For instance, ref. [33] tested different machine learning algorithms to predict the spread of wildfires and concluded that Decision Tree Regression is the best-performing. Good performances were already achieved with machine learning. However, more efficient models were developed leveraging deep learning architectures. Deep learning models capture the complex nature of fire spread by leveraging multimodal data. Different deep learning techniques, such as convolutional neural networks (CNNs), convolutional recurrent networks (CRNs), transformers, reinforcement learning, and graph neural networks, have been used to model fire spread behavior. One of the more efficient models, a multi-kernel convolutional neural network [7], achieved an excellent accuracy of 98.6% on the benchmark dataset Next Day Wildfire Spread [35]. In general, hybrid models have been widely explored and perform well in capturing the spatial and temporal resolution of fire spread. For example, A model proposed by Masrur et al. [8] combined a CNN architecture with a Long Short Term Memory and incorporated self-attention showed an F1-score of 96% regarding wildfire spread prediction. Some models are stacked one after the other [47,51] or embedded in a fire management framework [18].

Each architecture presents its capabilities and advantages. The choice of one architecture or another depends on the dataset, the context of use, and the application. Machine learning techniques excel with smaller datasets, such as in [30], providing robust performance with tabular data such as weather and vegetation metrics. Machine learning models are also faster to train, and are less complex and more interpretable, as showed in approaches like TOB [28]. As for deep learning architectures, each architecture has its advantages. CNNs are excellent for spatial feature extraction from satellite imagery and processing high-dimensional data effectively. CRNs capture effectively both spatial and temporal dependencies, making them ideal for wildfire spread prediction, as demonstrated for example in [49]. Transformers handle long-range dependencies well. GNNs are efficient for irregular features and representing details. RL models adapt to evolving scenarios and can optimally learn strategies for dynamic fire spread management. In conclusion, to predict wildfire spread, ML models are easier to train with small datasets and tabular data. On the other hand, DL models are good at handling high-dimensional data like satellite images, excel at capturing both spatial and temporal dynamics and are scalable to large datasets.

The introduction of machine learning and deep learning has revolutionized the research on wildfire spread prediction and brought astounding performance. Yet, emerging deep learning architectures such as foundation models and State Space Models (SSMs) could bring new insights into the field and remain to be explored.

8.2. Integration of Explainability into Wildfire Spread Models

The use of machine learning and deep learning in wildfire spread permits remarkable performance. However, without the use of Explainable Artificial Intelligence (XAI), the "black box" nature of such models causes trust and interpretability issues. Explainable artificial Intelligence involves understanding the process of transforming inputs into outputs in machine learning and deep learning models. For example, ref. [28] used a model that avoids the use of hidden layers to enhance transparency. Ref. [46] introduced a CNN with ASPP to understand the input values at play in the general and detailed patterns of wildfire spread prediction. The authors also use the Gradient-weighted Class Activation Mapping (Grad-CAM) algorithm to visualize feature importance across the model's layers. Ref. [59] employed the SHAP to quantify each input feature contributions to the predictions of the model. That kind of explainable architecture fosters trust in the model and aids in strategic fire management by clarifying fire authorities on the factors that influence the most wildfire spread. Fire management authorities can use this valuable information to develop policies in high-risk areas by managing vegetation or improving moisture, for example. In addition, insights from explainable models on the most influential factors of wildfire spread also help authorities to plan proactive measures like controlled burns, evacuation strategies, or wildfire extinguishing strategies. Improving the explainability and transparency of wildfire spread prediction models is crucial to helping fire management authorities make better-informed decisions.

8.3. Designing Real-Time and Light-Weight Models

Real-time prediction is crucial in fire management strategies due to wildfire's dynamic and rapidly evolving nature. Real-time decision-making in emergencies might help avoid catastrophic consequences. Several studies tackle this issue by proposing real-time or near real-time solutions [50,51]. In addition, light-weight models offer speed and need low computation power, making them essential in remote areas. They can easily be embedded in edge devices and help make real-time decisions, especially with constrained resources. Researchers in wildfire spread prediction have designed low comupational models to predict fire behavior and fire spread [16,37,39,40,67]. Developing a real-time and lightweight model that maintains a trade-off between performance and computational cost is imperative to help mitigate wildfire spread. Nonetheless, there are some challenges related to deploying real-time and low-computation models in dynamic wildfire events. Real-time prediction requires that the model receive frequent data updates. Data collection or transmission delays might affect the model's prediction accuracy. In addition, ensuring that the model's accuracy remains accurate while frequently receiving new data is difficult. To address these challenges, it is crucial to use multiple data sources, for example, satellites, drones, and ground sensors, and to develop user-friendly interfaces on mobile devices for field staff to input real-time data to enhance the accuracy of predictions. Moreover, data-driven modeling techniques that can process data in real-time should be privileged.

8.4. Improving Model Generalizability

Machine learning and deep learning models perform well in predicting fire spread. Yet, they need to generalize better to unseen data. Those models are often trained on a specific region with specific geographical and weather conditions, leading to a performance decrease if tested on different areas. However, wildfires are becoming increasingly frequent and are a global issue. Some studies have designed a global model for fire spread prediction.

For instance, Rösch et al. [68] proposed a country-scale and a continental-scale model. Although the performances were insufficient due to inadequate reference data quality, the continental model successfully learned the typical patterns of wildfire spread with comparable performance across different fire-prone Mediterranean countries. Techniques such as transfer learning should be explored to help models generalize better on unseen data. Moreover, datasets covering larger geographical regions across multiple countries should be developed. More insights on this is explored in Section 8.5. Generalizable models are needed to understand the familiar drivers of fire spread and to effectively mitigate wildfire spread across the world.

8.5. Enhancing Wildfire Spread Datasets and Metrics

High-quality data are essential to build efficient and reliable machine learning and deep learning models for fire spread prediction. Alongside historical fire mapping, burnt area, fire perimeters, and other fire variables, datasets for fire spread prediction typically encompass a diverse range of influential factors such as weather data (humidity, precipitation, temperature, wind speed, and direction, etc.), vegetation data (vegetation type, fuel load, fuel moisture content, Leaf Area Index, vegetation greenness, etc.), topography data (slope, aspect, elevation, and surface roughness), and anthropogenic variables (population density, road networks, etc.). Some datasets are tabular with data points [26,36,70,71,73], while others include multi-dimensional remote sensing data and satellite images [35,60,80,82]. Some datasets are benchmarks for fire spread prediction models [26,35]. Moreover, certain studies use generated data to train their model using simulators such as [13,15], and then test the model on real historical fires. This approach could be leveraged to improve the model's transferability and generalizability.

Datasets used in wildfire spread prediction present some challenges. Datasets often have quality deficits, with missing or sparse data for critical features like real-time vegetation moisture levels or wind direction. There are also spatial and temporal resolution discrepancies among sources, which complicate model training. While helpful in addressing data scarcity, simulated datasets may not fully capture real-world wildfire dynamics, potentially leading to model bias. To address those challenges, it is crucial to improve labeling and annotation on datasets and use expert annotations to improve the reliability of ground truth labels, especially for high-stakes tasks like fireline predictions. Data collection should also leverage multisource data and expand geographical and temporal coverage. Collecting data from underrepresented regions prone to wildfires helps to improve model generalizability. In addition, collaboration should be a priority. Fire management agencies, research institutions, and private organizations should partner to pool resources and data, and citizens should be encouraged to contribute by reporting fire incidents through mobile apps, for example. While datasets often include environment context, and weather variables, recording fire management interventions should be prioritized to model the impact of interventions and to develop more efficient firefighting strategies.

The metrics used to assess machine learning and deep learning models often depend on the dataset and the application. The use of task-specific metrics can make it difficult to compare models across studies. Therefore, it is crucial to use composite metrics to combine spatial, temporal, and accuracy-based evaluations. In addition, adding human-centric metrics should be explored to align with real-world firefighting needs. Operational metrics such as decision accuracy, the count of how often predictions align with decisions made by fire managers, and lead time, the time window provided by predictions for proactive firefighting efforts, could be helpful in bringing insights to practical scenarios.

The development and availability of quality datasets and metrics for benchmarking should be prioritized to build high-performing models and to better comparisons for wildfire spread prediction.

9. Conclusions

This study presented a comprehensive literature review highlighting the ML and DL techniques developed for wildfire spread prediction. The ML and DL techniques achieved significant performance compared to traditional models. In addition, we introduced the most common datasets employed to predict fire propagation. The use of machine learning approaches combined with traditional models or standalone models shows performance improvement. However, deep learning models exhibit the best and most significant accuracy in terms of fire spread prediction. Different DL techniques are explored, such as CNNs, CRNs and time series models, transformers, reinforcement learning, and graph neural networks. So far, CNNs and CRNs achieved the best results with up to 98.6% accuracy. However, it is difficult to compare model performances because they use different datasets and metrics. This is exacerbated by the lack of high-quality data and benchmark datasets, preventing the design of reliable and generalizable models. Future work could examine real-time and lightweight models. This direction might also lead to more explainable and interpretable models, allowing easier integration in real fire management frameworks. In addition, novel deep learning techniques remain to be investigated, such as foundational models and State Space Models.

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Abbreviations

The following abbreviations are used in this manuscript:

ML	Machine Learning
DL	Deep Learning
CNNs	Convolutional Neural Networks
CRNs	Convolutional Recurrent Networks
FBP	Canadian Forest Fire Behavior Prediction System
EML	Extreme Machine Learning
CA	Cellular Automaton
ConvLSTM	Convolutional Long Short-Term Memory
RL	Reinforcement Learning
MAE	Mean Absolute Error
RMSE	Root Mean Squared Error
MAPE	Mean Absolute Percentage Error
IoU	Intersection over Union
IoT	Internet of Things
LSSVM	Least Squares Support Vector Machines
FFSBP	Forest Fire Spread Behavior Prediction
FFSPP	Forest Fire Spread Process Prediction
FFSRP	Forest Fire Spread Results Prediction
TOB	Transparent Open Box
MBE	Mean Bias Error
ANN	Artificial Neural Network
SVMs	Support Vector Machines

FFMC	Fine Fuel Moisture Code
DMC	Duff Moisture Code
DC	Drought Code
ISI	Initial Spread Index
NDVI	Normalized Difference Vegetation Index
GIS	Geographic Information Systems
DCIGN	Deep Convolutional Inverse Graphics Network
SSTDF	Spread Spatiotemporal Distribution Field
VIIRS	Visible Infrared Imaging Radiometer Suite
WAM	Wildfire Assessment Model
ASPP	Atrous Spatial Pyramid Pooling
DR	Dilation Rate
Grad-CAM	Gradient-weighted Class Activation Mapping
LRCN	Long-term Recurrent Convolutional Neural Network
MDP	Markov Decision Process
LSTM	Long Short-Term Memory
UAV	Unmanned Aerial Vehicle
BiLSTM	Bidirectional Long Short-Term Memory
GNP	Golestan National Park
MODIS	Moderate Resolution Imaging Spectroradiometer
DEM	Digital Elevation Model
SHAP	SHapley Additive exPlanations
ASUFM	Attention Swin U-net with Focal Modulation
3DCNN	Three-dimensional Convolutional Neural Network
MIoU	Mean Intersection over Union
MA-Net	Multi-Attention Network
MCTS	Monte Carlo Tree Search
A3C	Asynchronous Advantage Actor-Critic
IGN	Irregular Graph Network
WFDNN	Wildfire Deep Neural Network
STGNN	Spatiotemporal Graph Neural Network
BUI	Buildup Index
FWI	Fire Weather Index
FRP	Fire Radiative Power
DoB	Date of Burning
SSMs	State Space Models
XAI	Explainable Artificial Intelligence

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