

From Black Box to Insight: Explainable AI for Extreme Event Preparedness

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Abstract—As climate change accelerates the frequency and severity of extreme events such as wildfires, the need for accurate, explainable, and actionable forecasting becomes increasingly urgent. While artificial intelligence (AI) models have shown promise in predicting such events, their adoption in real-world decision-making remains limited due to their black-box nature, which limits trust, explainability, and operational readiness. This paper investigates the role of explainable AI (XAI) in bridging the gap between predictive accuracy and actionable insight for extreme event forecasting. Using wildfire prediction as a case study, we evaluate various AI models and employ SHapley Additive exPlanations (SHAP) to uncover key features, decision pathways, and potential biases in model behavior. Our analysis demonstrates how XAI not only clarifies model reasoning but also supports critical decision-making by domain experts and response teams. In addition, we provide supporting visualizations that enhance the interpretability of XAI outputs by contextualizing feature importance and temporal patterns in seasonality and geospatial characteristics. This approach enhances the usability of AI explanations for practitioners and policymakers. Our findings highlight the need for AI systems that are not only accurate but also interpretable, accessible, and trustworthy, essential for effective use in disaster preparedness, risk mitigation, and climate resilience planning.

Index Terms—AI model, explainable AI, extreme events, wildfires, disaster preparedness

I. INTRODUCTION

The frequency and severity of extreme events, such as wildfires, heatwaves, and floods, have increased significantly due to climate change [1], [2], posing serious risks to ecosystems [3], public health [4], infrastructure [5], and communities. This urgency has led to growing use of AI and machine learning (ML) for spatiotemporal forecasting, such as wildfire and spread prediction [6].

Despite these advances, the real-world adoption of AI-driven forecasting tools in critical domains like disaster response remains limited. A key barrier is the “black-box” nature of many AI models, like deep neural networks, which make

accurate predictions but lack transparency. This poses serious challenges for decision-makers in high-stakes environments like emergency response, firefighting, and public safety. Without clear insight into why a model makes certain predictions, it becomes difficult to build trust, assess risks, validate outcomes, and effectively use model outputs in operations.

To address these challenges, our work adopts NASA’s FAIRUST principles [7], which emphasize that AI applications and data should be Findable, Accessible, Interoperable, Reusable, Understandable, Secure, and Trustworthy. We specifically focus on leveraging explainable AI (XAI) techniques to make complex model behavior more Understandable. XAI sheds light on how models use input features, revealing decision logic and potential biases. In the context of extreme event forecasting, such as wildfires, XAI helps bridge the gap between predictive accuracy and real-world usability, empowering domain experts to evaluate model trustworthiness, identify critical risk factors, and make well-informed decisions under conditions of uncertainty.

In this paper, we explore the use of XAI in wildfire forecasting, which is a critical and complex challenge in extreme event prediction. *Our contributions are threefold.* (1) We evaluate several state-of-the-art AI models and use SHapley Additive exPlanations (SHAP) [8] to interpret predictions, highlighting key features and enabling a deeper understanding of model behavior, strengths, and limitations. (2) To enhance interpretability, we introduce visualizations that map feature importance across spatial and seasonal dimensions, making AI-generated insights more accessible to non-technical stakeholders, including emergency planners and policymakers. (3) We show how these explainability tools can support actionable insights for extreme event preparedness, bridging the gap between model performance and operational utility. Our results emphasize the role of XAI in trustworthy climate risk forecasting and responsible AI research with societal impact.

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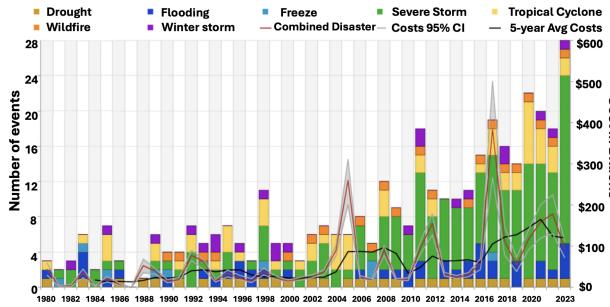


Fig. 1. Costs of U.S. extreme disaster events over time [9].

II. SYSTEMATIZATION OF EXTREME WEATHER EVENTS PREDICTION AND EXPLANATION

A. Extreme Weather Events

Extreme weather events, such as wildfires, heatwaves, hurricanes, floods, and droughts, are statistically rare but highly impactful phenomena that deviate significantly from normal conditions [4]. Their impacts and associated costs have been rising, reaching hundreds of billions of dollars in recent years in the U.S. [9] (Figure 1). In 2024, the National Oceanic and Atmospheric Administration (NOAA) reported 27 U.S. weather and climate disasters, each causing over one billion in damages [10]. Climate change has increased the frequency and severity of these events by warming the atmosphere, which holds more moisture and intensifies heat and precipitation extremes [11]. These escalating costs and increasing frequency and intensity of extreme events have motivated significant research into understanding and predicting extreme events [6]. Skillful forecasts are crucial for mitigation, adaptation, early warning systems, and building resilience in vulnerable communities. However, the chaotic nature of the climate system and its complex interactions across atmospheric, oceanic, and land processes pose major challenges for reliable prediction.

Wildfires are among the most destructive extreme events, becoming more frequent and intense due to climate change and drawing increased scientific attention. These complex phenomena are influenced by weather conditions (e.g., temperature, humidity, wind) and human activity. Wildfires can threaten lives, infrastructure, ecosystems, and economies [12]. Advancing wildfire understanding and prediction is, therefore, essential and forms the focus of this paper.

B. AI for Extreme Weather Events Prediction

Despite challenges in predicting extreme weather, advances in understanding its dynamics and development of physics-based models have improved forecast skills in recent decades [13], [14]. Recent AI/ML developments have further transformed forecasting by leveraging diverse data. Models such as Tree-based Ensemble, Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), and Transformer have shown promise in detecting extreme weather patterns, aiding predictions of storms, floods, heatwaves, and wildfires. Ensemble and tree-based models (e.g., Random Forests, Gradient

Boosting) are widely applied to floods, heatwaves, and severe storms, offering robustness to noisy data and supporting uncertainty quantification [15], [16]. Temporal models like RNNs, Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU), are well-suited for capturing long-term dependencies in sequential weather data, aiding in the prediction of events such as heatwaves and droughts [17], [18]. More recently, Transformer-based models with attention mechanisms have shown strong performance by dynamically weighting relevant meteorological features and time steps, improving forecasts of complex events like heatwaves and hurricanes [19].

Physics-based models like WRF-Fire [20] are widely used but computationally expensive and sensitive to initial conditions. Meanwhile, AI/ML models address these limits by capturing complex, nonlinear patterns [6]. We focus on AI for wildfire prediction, one of the most challenging forecasting tasks, where accurate timing and location are vital. Beyond prediction, we examine interpretability and forecasting opportunities, which remain underexplored.

C. XAI for Extreme Weather Events Prediction

Despite their advantages, AI models often lack transparency due to their “black-box” nature, posing challenges for operational deployment. This underscores the need for XAI, which helps identify key features and patterns behind predictions. In climate science, interpretability not only fosters user trust but also uncovers insights consistent with physical understanding [6]. XAI methods to explain AI-driven forecasts for extreme weather events generally fall into two categories (Figure 2): intrinsic interpretable model designs and post-hoc techniques.

First, intrinsic XAI methods rely on models that are transparent by design [21]. Examples include linear regression, which shows feature influence via coefficients [22], and decision trees or random forests, which reveal decision paths through feature thresholds [23], [24]. These models are often used in extreme event prediction due to their simplicity and interpretability. Attention-based deep learning models can also be intrinsically interpretable. For example, [25] uses a Transformer with multi-head self-attention to identify key temporal and spatial drivers in next-day wildfire prediction.

Second, post-hoc XAI methods are applied after model training to explain predictions from complex AI/ML models. Common techniques include feature attribution like SHAP [8], LIME [26], surrogate model [27], counterfactual explanations [6], [28], and visualization-based methods [29], [30]. SHAP is widely used in climate science for offering both global and local interpretability. In extreme weather forecasting, SHAP reveals key atmospheric features, enhancing trust and insight [31]. It helps assess wildfire risk [24] and finds critical factors like humidity and wind [32].

Most extreme weather prediction studies favor post-hoc XAI methods, as they explain complex AI models better than inherently interpretable models. Since high-performing models are often opaque, post-hoc tools like SHAP provide critical insights, build trust, and support informed planning [33]. In this

work, we use SHAP to interpret wildfire predictions, ensuring explanations are physically meaningful and informative.

III. BACKGROUND

A. AI Prediction Models

To predict extreme events, AI models typically use multiple weather and atmospheric features over a period preceding the event. Each feature x_i is a time series $\{x_{it}\}_{t=1}^L$, where L is the length of the time window. An input sample x consists of time series data of all N features, denoted as $x = \{x_i\}_{i=1}^N$. This formulation captures the evolving dynamics of multiple environmental factors over time, which are essential for modeling complex phenomena like wildfire occurrence.

An AI model prediction $f(x)$ takes a time series x as input and produces a binary prediction $y \in \{0, 1\}$, where $y = 1$ indicates the predicted occurrence of a wildfire, and $y = 0$ denotes the absence of wildfire risk on the prediction day. This binary classification setting is commonly used in operational wildfire forecasting systems, where timely and accurate predictions can support early warning efforts and inform mitigation strategies. By tracking changes in temperature, humidity, wind, and precipitation over time, AI models identify patterns that may warn of a higher risk of wildfires. Incorporating time series structure allows the model to consider the current environmental state and to account for trends, lags, and cumulative effects that develop over the preceding days or weeks.

B. Model Explanations and SHAP

The goal of model explanations is to improve transparency, interpretability, and trust in ML models by capturing how each feature influences the model's decisions and which class such decisions favor. XAI methods address this by providing human-understandable reasons for model behavior. SHapley Additive exPlanations (SHAP) [8] is a widely used XAI method. Given a sample $x = \{x_i\}_{i=1}^N$ where x_i represents the i^{th} feature and N is the number of features, and a prediction model f that outputs the probability $f(x)$ of x belongs to a certain class y , SHAP can be represented as a linear model of the form $g(x) = \sum_{i=1}^N e_i x_i$, where $\{e_i\}_{i=1}^d$ are the resulting coefficients of the explanation model $g(x)$, measuring the impact of x_i on the model's decision. In general, higher values of e_i imply a higher impact of x_i in the model decision.

IV. TRANSPARENT WILDFIRE MODELING: INSIGHTS THROUGH XAI

In this section, we shed light on how XAI can enhance our understanding of wildfire predictions and support preparedness activities. To achieve this, we examine different AI models and use SHAP with an adjusted visualization to interpret the outputs of these models. Our analysis reveals 1) how different AI models make decisions regarding wildfire risk, 2) which features drive predictions, and 3) how insights into these contributing factors can inform and improve preparedness strategies. By revealing the internal reasoning of AI models, XAI empowers decision-makers to move beyond black-box predictions toward transparent preparedness planning. The

insights derived from this analysis can guide more effective strategies for wildfire mitigation and emergency management.

A. AI Models for Wildfire Prediction

To ensure generalizable analysis, we employ various AI models widely used for wildfire prediction, including *deep learning models*, i.e., LSTM, Transformer, GTN, and *tree-based models*, i.e., Random Forest and XGBoost. They capture complex temporal patterns in wildfire data and allow comparison of accuracy and interpretability across architectures.

LSTM is a recurrent neural network designed to capture long-term dependencies using gating mechanisms, making it effective for sequential data like wildfire events [59]. Transformer models rely on self-attention rather than recurrence to model sequence dependencies; we adopt an encoder-only version for wildfire risk prediction [60]. GTN extends the Transformer by adding dual attention, making it well-suited for multivariate time-series data in environmental settings [61]. We also include two ensemble tree-based models, including Random Forest and XGBoost, known for handling noisy and heterogeneous data. Random Forest uses multiple decision trees with majority voting to improve robustness [62], while XGBoost builds trees sequentially to refine predictions, improving accuracy and efficiency.

We train deep learning models using the Adam optimizer with the following settings: LSTM with a learning rate (lr) of 0.004 and a weight decay (wc) of 0.0063, Transformer with $lr = 0.0001$ and $wc = 0$, and GTN with $lr = 0.0012$ and $wc = 0.0045$. All models run for 30 epochs with a 0.1 learning rate decay every 15 epochs. We adopt model architectures and training pipelines from the open-source Mesogeos project [63]. For the tree-based models, we use `sklearn` implementations with 100 trees each. Random Forest uses Gini impurity with a minimum split size of 2 and no depth limit, while XGBoost uses a learning rate of 0.3 and a max depth of 6.

B. Dataset

We conducted our analysis of wildfire prediction and XAI using two datasets from distinct geographical regions. The diverse approach allows us to examine how wildfire prediction may vary across different regions, particularly in terms of feature importance, and to draw broader, more generalizable insights for preparedness and mitigation.

1) *General Information:* The Mesogeos dataset is a large-scale dataset for wildfire modeling in the Mediterranean [63]. We use its wildfire danger forecasting subset, containing 25,722 samples: 19,353 for training, 2,262 for validation, and 4,107 for testing. Each sample includes 24 features over 30 days prior to a wildfire event, split into static (i.e., values remain the same for all days within a sample) and dynamic (i.e., values might change daily) types. Table I provides the full name and explanations for each feature in this dataset.

The California Wildfires dataset covers weather conditions and wildfire occurrences in California from 1984 to 2025 [64]. The dataset includes nine feature groups, with seasons one-hot encoded. Table II provides the full name for each feature in this

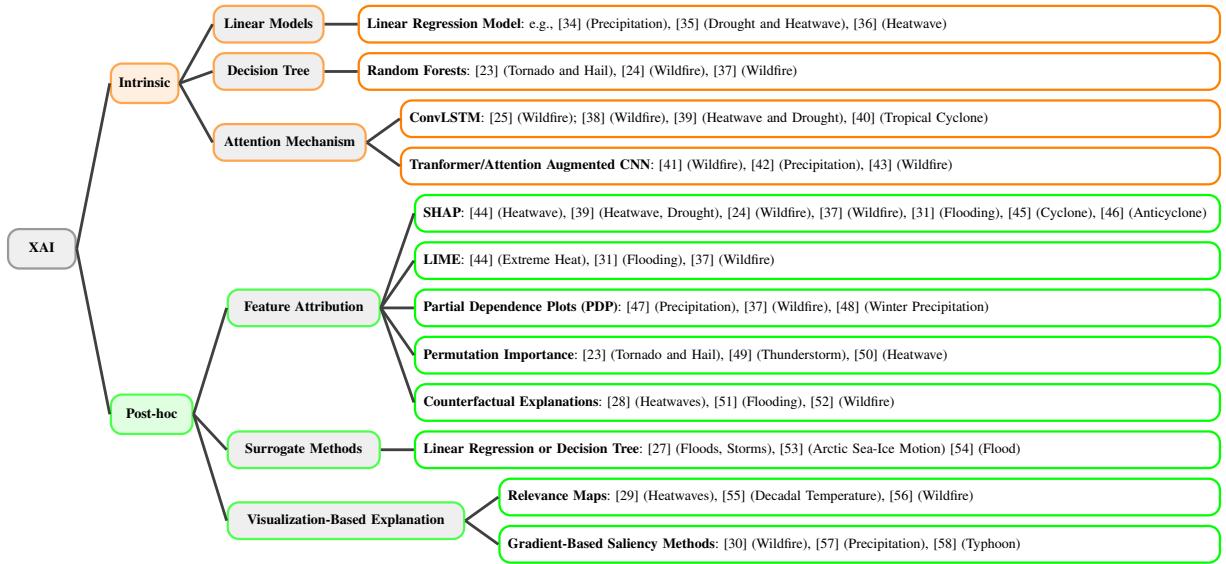


Fig. 2. Explainable AI (XAI) Techniques.

dataset. A total of 14,976 observations are grouped into 1,248 samples, each representing an 11-day window preceding a wildfire event. Among them, 998 samples are used for training and 250 samples for testing.

When performing XAI analysis with each dataset and each AI model, we only used samples that were correctly predicted as wildfire occurrences by the model in question. This sample selection is used to ensure that the results presented in our final visualizations are both consistent and reliable.

2) *Exploratory Data Analysis: In the Mesogeos dataset*, six features have missing values across multiple samples. Table III presents their average percentage of missing values, with `1st_day` and `1st_night` missing in about one-third of the total entries. The original preprocessing pipeline filled missing values with zeros [63], but for temperature features in Kelvin, this implies absolute zero, which is a physically unrealistic condition. To address this, we impute missing values using the mean of each feature calculated from the training set. While this method introduces noticeable skewness, particularly in `1st_day` and `1st_night`, mean imputation is more physically plausible than zero-filling and does not significantly degrade data utility. In fact, random checks with the LSTM, Transformer, and GTN models show higher accuracy using mean imputation compared to zero-filling. Another feature with similar skewness is `smi`, with 6.83% of its values imputed. Other dynamic features (e.g., `ndvi`, `rh`) follow near-Gaussian distributions, while static features (e.g., land cover, population) cluster near zero, reflecting the Mediterranean landscape (Figure 3).

In the California Wildfires dataset, there are a total of 11 features, comprising 8 original features and a one-hot encoded `season` feature represented by three mutually exclusive binary variables: `season_winter`, `season_spring`, and `season_summer`. Features such as precipitation, maximum temperature (`max_temp`), min-

imum temperature (`min_temp`), and average wind speed (`avg_wind_speed`) are treated as independent. Other features are derived or correlated, such as `temp_range` (from `max_temp` and `min_temp`) and `wind_temp_ratio` (from `avg_wind_speed` and `max_temp`). Lagged features are computed over a 7-day window. The seasonality variables are mutually exclusive: if `season_summer` is 1, then `season_winter` and `season_spring` are 0, and vice versa. This dataset has one day with missing values in `precipitation`, `min_temp`, `max_temp`, and `temp_range`. Additionally, there are 12 missing entries in `avg_wind_speed`, which also affect `wind_temp_ratio`. We impute missing values in the independent features using their global means. Missing `temp_range` and `wind_temp_ratio` values are calculated using data from their defining features. Looking deeper into the dataset, the independent features `min_temp`, `max_temp`, and `avg_wind_speed` exhibit roughly Gaussian distributions. Both `max_temp` and `avg_wind_speed` are right-skewed, while `min_temp` is slightly left-skewed and bimodal, reflecting seasonal temperature shifts. The remaining independent feature, `precipitation`, is highly skewed, with 90.78% of values equal to zero, producing a near-uniform distribution mirrored in its lagged version. Derived features such as `temp_range`, `wind_temp_ratio`, and `lagged_avg_wind_speed` are also right-skewed. Seasonality features are uniformly distributed, with each binary variable set to 1 in roughly 25% of samples. Figure 4 shows representative distributions in this dataset.

C. Visualizing the Temporal Evolution of SHAP Values

In this study, we leverage the SHAP framework [8] to explain wildfire predictions. While default SHAP visualizations, such as bar or summary plots, are effective for static data, they are inadequate to capture the temporal dynamics of time series.

TABLE I
FEATURES IN THE MESOGEOS DATASET.

Features	Abbreviation	Full name
Static	population, slope, dem, roads_distance	Population, Slope, Elevation, Distance from roads
	lc_wetland, lc_shrubland, lc_grassland	Area of wetland, shrubland, grassland
	lc_water_bodies, lc_forest	Area of water bodies, forest
	lc_sparse_vegetation	Area of sparse vegetation
	lc_settlement, lc_agriculture	Area of settlement land, agricultural land
Dynamic	wind_speed, ssrd	Wind speed, Surface solar radiation downwards
	tp, sp, rh	Total precipitation, Surface pressure, Relative humidity
	t2m, d2m, lst_night, lst_day	2-meter temperature, Dewpoint temp., Night's and day's land surface temp.
	smi, lai, ndvi	Soil moisture index, Leaf area index, Normalized difference vegetation index

TABLE II
FEATURES IN THE CALIFORNIA WILDFIRES DATASET.

Name	Explanation
precipitation, lagged_precipitation	Daily precipitation, Cumulative precipitation over the preceding 7 days
max_temp, min_temp, temp_range	Maximum daily temp., Minimum daily temp., Daily temperature range
avg_wind_speed, wind_temp_ratio, lagged_avg_wind_speed	Average daily wind speed, Ratio of average wind speed to max temp.
lagged_avg_wind_speed	Average wind speed over preceding 7 days
season	The season of the observation (Winter, Spring, Summer, Fall)

TABLE III
PERCENTAGE OF MISSING VALUES ON SEVERAL FEATURES IN THE MESOGEOS DATASET.

Feature	lst_night	lst_day	smi	lai	ndvi	population
Percentage (%)	36.43	31.49	6.83	1.69	0.25	0.01

Specifically, they do not show how the influence of individual features evolves over time, which is crucial for understanding sequential patterns leading to wildfire events and identifying potential forecast opportunities.

To address this limitation, we extract SHAP values for each feature across multiple time steps and create a custom scatterplot visualization. For each feature, we plot its SHAP values over the days leading up to a wildfire event, such as 30 days for the Mesogeos dataset and 11 days for the California Wildfires dataset. In this plot, dot color and size represent the direction and magnitude of the feature's impact, respectively. Using a blue-white-red colormap, blue dots indicate negative SHAP values, white represents near zero, and red denotes positive values. Dot size is proportional to the absolute SHAP value, emphasizing more influential contributions. This visualization provides a clearer and more intuitive view of how key features affect model decisions over time, supporting more informed and actionable wildfire preparedness.

D. Experimental Results

1) *Prediction Performance* : Table IV presents the prediction accuracy of five AI models evaluated on the Mesogeos and California Wildfires datasets. Deep learning models consistently outperform tree-based ensemble models across both datasets. On the Mesogeos dataset, the Transformer achieves the highest accuracy at 87.53%, followed closely by LSTM (87.00%) and GTN (86.34%). In contrast, Random Forest and XGBoost perform worse, with accuracies of 77.23% and 75.00%, respectively. We observe a similar trend on the California Wildfires dataset, although the overall accuracies are lower due to its smaller size and higher variability. The Transformer again leads with 78.71% accuracy, followed by GTN (77.60%) and LSTM (73.49%), while Random Forest

and XGBoost achieve 76.31% and 71.89%, respectively. These results highlight the strength of deep learning models, particularly those based on attention mechanisms, in capturing the complex temporal patterns associated with wildfire prediction.

2) *SHAP Explanations and Visualization*: In this section, we enhance interpretability by visualizing SHAP values over time, showing how features influence wildfire predictions across sequential steps. We apply this to multiple AI models and both datasets, offering general insights here and detailed analysis in Section IV-E.

Mesogeos Dataset. Figure 5 presents the average SHAP values across all samples in the Mesogeos dataset using an LSTM prediction model. Different from other visualizations [24], [37], we display all 24 features over a 30-day window. Overall, key features driving the model's wildfire predictions include 2-meter air temperature (t_{2m}), relative humidity (rh), daytime and nighttime land surface temperature (lst_day , lst_night), and total precipitation (tp). Conversely, dew-point temperature ($d2m$), soil moisture index (smi), and elevation (dem) negatively impact predictions, indicating lower wildfire likelihood. Other features, such as land cover classes, had minimal influence and are excluded from later figures to focus on more significant contributors. As expected, data closer to the prediction date have greater impact; for instance, when predicting day 31, weather data from day 25 onward contribute most. Figure 6 shows how the importance of the top five features evolves over time, with notable changes beginning around day 28, matching the increased SHAP magnitudes seen in Figure 5. Feature importance also varies across individual cases, suggesting the model's reliance on certain features depends on temporal and environmental context. While some features show strong average effects, their impact can shift

TABLE IV
ACCURACY (%) OF MODELS TRAINED ON MESOGEOS AND CALIFORNIA WILDFIRES DATASETS.

Model		LSTM	Transformer	GTN	Random Forest	XGBoost
Accuracy	Mesogeos	87.00	87.53	86.34	77.23	75.00
	California Wildfires	76.80	78.71	77.60	76.31	71.89

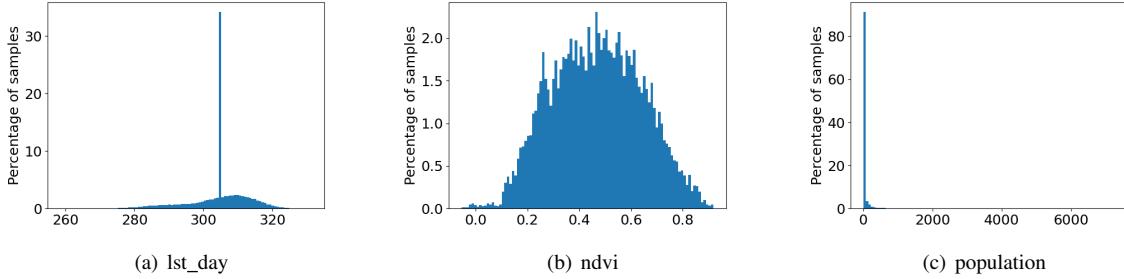


Fig. 3. Representative feature distributions from Mesogeos dataset.

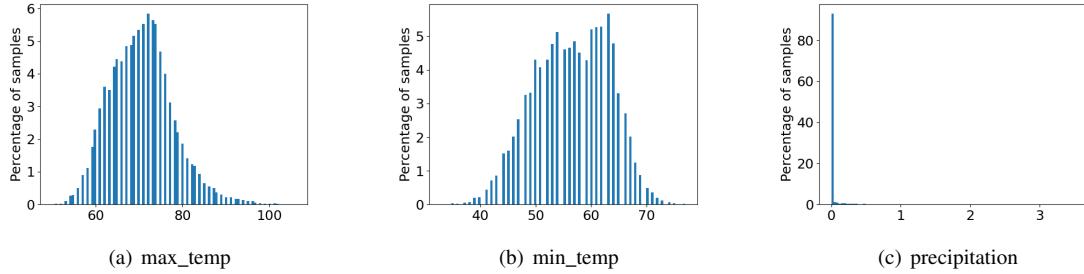


Fig. 4. Representative feature distributions from California Wildfires dataset.

based on local conditions, highlighting the model’s dynamic behavior and the value of SHAP for uncovering such nuances. Furthermore, the explanations generated by the Transformer-based models are consistent with the aforementioned observations with LSTM (Figure 7).

In tree-based methods such as Random Forest and XGBoost, the evolution of feature contributions over the 30-day window differs from that of the deep learning models (i.e., LSTM, Transformer, GTN) when predicting wildfires on day 31. In Figure 8, contributions come not only from the later days (e.g., day 25 onward) but also from earlier days, such as day 2 in `ssrd` or day 5 in `1st_night`. The root cause is that the Random Forest and XGBoost models do not use every feature at every time step for node splits. As a result, some features may receive SHAP values of zero on certain days. Despite these model architecture and temporal differences, the key features with the highest SHAP values remain largely consistent. In particular, temperature-related features continue to show strong correlations with wildfire risk across all models.

California Wildfires Dataset. We observe similar patterns in the California Wildfires dataset, where later days in the time window have a greater influence on wildfire predictions compared to earlier days. In addition, explanations from deep learning models (Figure 7b) slightly differ from those of tree-based models (Figure 8b). Similar to the Mesogeos dataset,

temperature-related features also have the strongest impact on the model’s predictions. SHAP values from individual samples show evolution consistent with the average SHAP values across the test set. Furthermore, explanations indicate that spring generally contributes the least to wildfire predictions, meaning a lower wildfire risk during this season.

E. Discussions

1) Wildfire Prediction across Datasets and AI Models:

Across both datasets and all AI models, we observe several consistent patterns. First, temperature-related features contribute most significantly to wildfire predictions across all cases. In the Mesogeos dataset, relative humidity also plays a major role in model decisions, while in the California Wildfires dataset, seasonality emerges as a key influencing factor. Second, the temporal evolution of feature importance differs slightly between deep learning and tree-based models, and among deep learning models themselves. Whereas deep learning models tend to assign greater importance to later days, tree-based models rely on both later and some earlier days. This suggests that tree-based models such as Random Forest and XGBoost may be less effective in capturing temporal dynamics, even if they identify important features consistent with those found by deep learning approaches.

In addition, different from LSTM, the Transformer model can extract meaningful signals from both the start and end

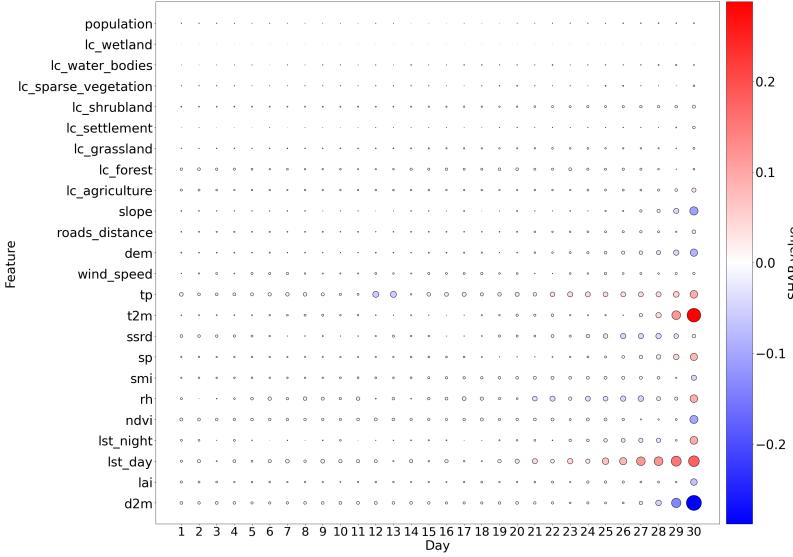


Fig. 5. Visualization for *average* SHAP values for the Mesogeos dataset using the LSTM model.

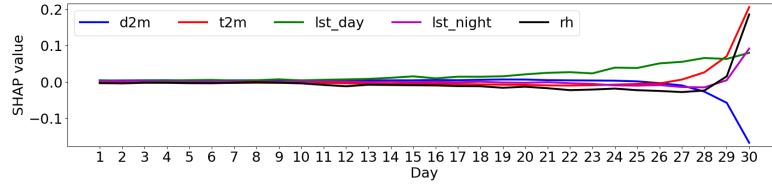


Fig. 6. SHAP value evolution in the top five important features (Mesogeos and LSTM model).

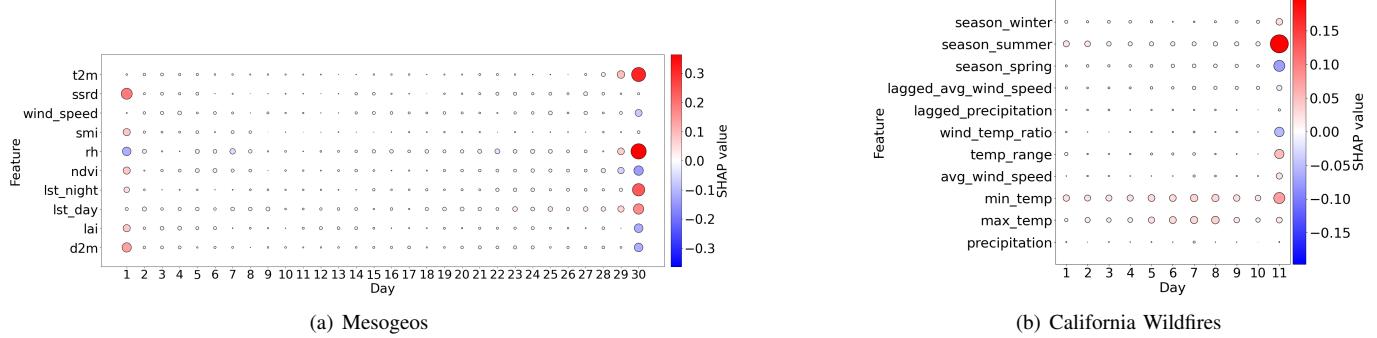


Fig. 7. Average SHAP values in the Transformer model across datasets.

of the input sequence. In Figure 7a, features such as `ndvi`, `lst_night`, and `d2m` in the Mesogeos dataset exhibit relatively high absolute SHAP values on both the first day and last day of the time window. Other variables, such as `ssrd` and `smi`, have lower SHAP values by the last day, but retain their overall positive contributions to model's decisions. This pattern is less pronounced in models trained on the California Wildfires dataset, likely due to its shorter time window and fewer samples. Consequently, Transformers trained on California data may lack the temporal depth to learn patterns similar to those from Mesogeos, resulting in different trends.

2) *Seasonality of wildfires:* In the California Wildfires dataset, SHAP explanations indicate that seasonality plays a significant role in predicting wildfire occurrence. Across

AI models, at least one season-related feature has a high SHAP value, with `season_summer` being the strongest in Transformer and Random Forest models. For the LSTM and GTN models, `season_summer` and `season_winter` have comparable impacts on model decisions. These results suggest a general consensus among the models that summer is the most fire-prone season, while certain winter conditions may also contribute to wildfire risk. However, California's diverse climate, with wide temperature and precipitation variation across regions and years [65]. Further investigation into this geographic and climatic variability can clarify seasonal wildfire patterns and improve model interpretations.

In the Mesogeos dataset, no features explicitly encode seasonality. To examine seasonal effects, we visualize av-

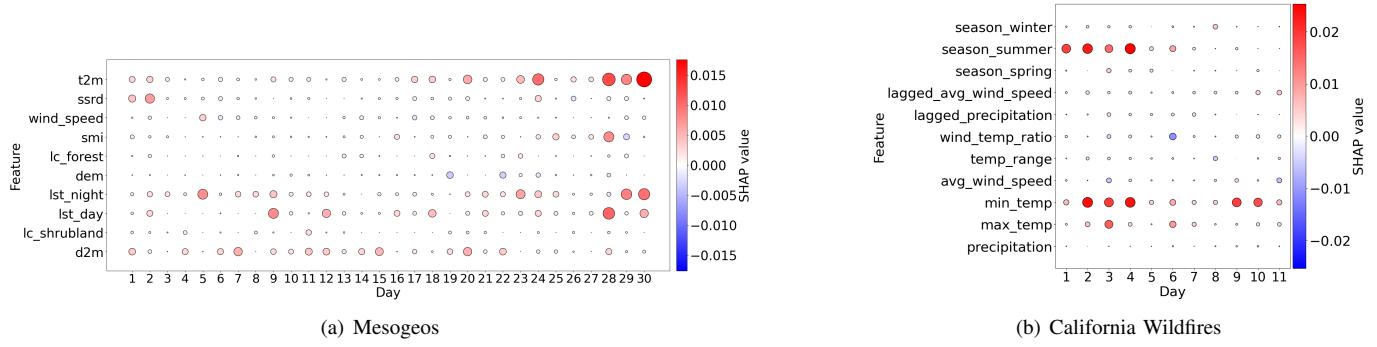


Fig. 8. Average SHAP values in the Random Forest model across datasets.

verage SHAP values by month (Figure 9). From April to August, which are typically considered the summer period, temperature-related features strongly contribute positively, while dewpoint temperature contributes negatively, , which is consistent with the known physical variables that contribute to wildfires. SHAP patterns vary by month, suggesting that wildfire risk factors change seasonally. Intuitively, higher temperatures and stronger winds increase wildfire risk, especially in summer, while more precipitation and higher dewpoint reduce it. During colder months, conditions affect fires differently. Our results show that precursors and forecasts vary by region and season, highlighting the need to incorporate temporal context in wildfire prediction and interpretation.

3) Forecast opportunities beyond weather time scale: Based on Section IV-D2, later days in the temporal window generally exert stronger influence on wildfire predictions, which is intuitive given that recent conditions are typically more relevant for forecasting. However, certain variables exert significant effects much earlier. For instance, in Figure 5, t_p and lst_day have high SHAP values as early as day 4, while in Figure 7b, max_temp and min_temp contribute meaningfully by day 3. These early signals suggest that some features encode lasting or cumulative influence, thereby extending wildfire predictability. Recognizing these signals strengthens early warning and long-term wildfire planning.

We further evaluate how this feature importance translates into model performance (Table V). Using the Transformer architecture, we trained models on subsets of features ranked by their importance derived from SHAP. Features with high absolute SHAP values were classified as the most important, while those with values near zero were considered the least important. When trained on only ten features, the model trained on the most important subset markedly outperformed the model trained on the least important subset, with an accuracy difference of 3.75%. Interestingly, this margin was larger than the performance gap between the full model (trained on all twenty-four features) and the model trained on the ten most important features (3.30%). In addition to accuracy gains, prioritizing high-impact features reduced computational cost. Training time decreased by 3.86 seconds per epoch when restricting the training set to ten features, corresponding to nearly two minutes saved over a thirty-epoch schedule,

while the model did not suffer significant performance degradation. Collectively, these findings underscore the value of explainability-guided feature selection: by emphasizing early and influential signals, forecasting models can achieve high accuracy at lower computational cost, ultimately supporting more timely and effective responses to extreme wildfire events.

4) Results validation using LIME: To complement the SHAP-based analyses, we further employed LIME [26] to interrogate our models' predictions. As shown in Figure 10, the LIME explanations broadly corroborate the SHAP results across multiple features. For instance, both methods identify smi as exerting a positive influence on wildfire prediction, while also capturing the early effects of rh and $d2m$. Notable discrepancies emerge for static features such as population and land cover classes, which is expected given that LIME was originally designed to explain local, instance-level predictions rather than global trends across the entire dataset. Nevertheless, the convergence of LIME and SHAP on key dynamic predictors underscores a degree of consistency between the two XAI approaches, reinforcing confidence in the interpretability of the models' outputs. LIME results are also aligned with physical understanding, given that land cover types can impact the occurrence of wildfires.

5) Implications for Mitigation and Emergency Management: Using SHAP to interpret wildfire predictions from various AI/ML models reveals that the feature contributions to wildfire likelihood generally align with the known physical understanding of wildfire occurrence, thereby increasing confidence and trustworthiness of AI/ML predictions. The insights gained from SHAP-based explanations offer actionable opportunities for improving wildfire mitigation and emergency response strategies. Across both the Mesogeos and California Wildfires datasets, temperature-related features emerged as the most influential predictors, reinforcing the importance of monitoring thermal conditions, such as 2-meter air temperature, day- and night-time land surface temperature, and dewpoint temperature, as part of early-warning systems.

By understanding how AI models respond to these factors over time, emergency management agencies can better align their decision-making processes with evolving risk conditions. For instance, deep learning models consistently identify later days in the time window as more impactful, indicating that

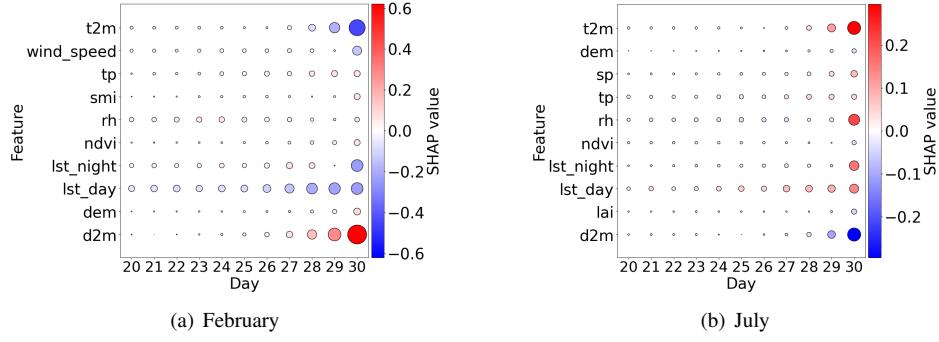


Fig. 9. Average SHAP values for wildfires in February and July (Mesogeos, LSTM model).

TABLE V

ACCURACY AND AVERAGE TRAINING TIME OF TRANSFORMER MODEL TRAINED ON DIFFERENT COMBINATIONS OF MESOGEOS FEATURES.

Feature combination	Top-5	Top-10	Top-20	Original (24 features)
Accuracy (%) (Most important)	80.99	83.86	86.83	87.16
Accuracy (%) (Least important)	73.90	80.11	85.63	87.16
Training time per epoch (seconds)	34.22	37.72	40.14	41.58

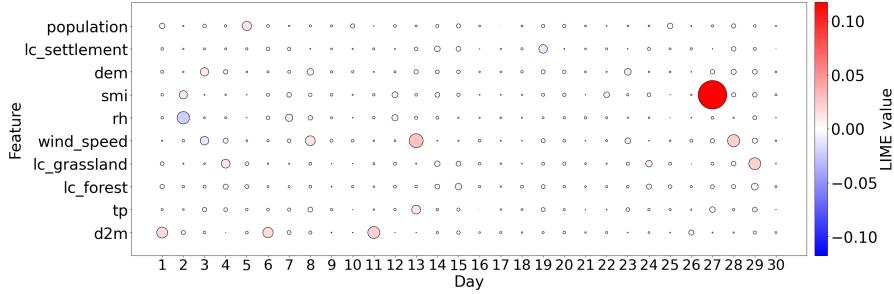


Fig. 10. Visualization for *average* LIME values for the Mesogeos dataset using the Transformer model.

real-time environmental monitoring in the days immediately preceding a potential fire event is crucial for accurate forecasting and rapid response. In addition, the presence of early signals could serve as triggers for proactive mitigation strategies, including: 1) Pre-deployment of firefighting resources to high-risk zones, 2) Public advisories and evacuation planning in vulnerable regions, and 3) Controlled burns or vegetation management ahead of peak fire risk periods.

Moreover, seasonal patterns revealed by model explanations provide guidance for long-term planning. For example, since most models agree that summer is the most fire-prone period, preparedness efforts should ramp up before summer. The different SHAP patterns in summer and winter months suggest that incorporating season-related features or temporal markers into prediction models could enhance both interpretability and effectiveness in operational settings.

Finally, the observed limitations of tree-based models in capturing temporal dynamics underscore the need for deploying temporal-aware architectures (e.g., LSTM, Transformer, GTN) in real-world applications where the timing of environmental signals is critical. Leveraging model explanations not only improves trust in AI predictions but also supports evidence-based policy decisions for wildfire risk mitigation and emergency response planning.

V. CONCLUSION

This paper investigated how existing XAI methods can improve understanding and interpretation of wildfire prediction models. By visualizing SHAP explanations across various AI models and two geographically distinct datasets, we found a consistent emphasis on temperature-related features, seasonal-related, and precipitation, etc. as key drivers of wildfire forecasts. While this aligns with domain knowledge, the early signals revealed by SHAP values offer valuable insights for early warning and emergency planning. These insights can help authorities anticipate wildfire risk well in advance, enabling more proactive resource allocation and mitigation strategies. Overall, our findings demonstrate the potential of explainable AI to enhance wildfire prediction reliability and support more effective disaster preparedness and response.

Following the NASA's FAIRUST principles, this work is grounded in public, verifiable data and will share code and methods to ensure the research is Findable, Accessible, Interoperable, and Reusable. Crucially, by focusing on making wildfire forecasting more Understandable through state-of-the-art XAI, we promote interpretability and reliability. Adopting FAIRUST principles advances transparency in AI for climate science while fostering open and accessible research.

REFERENCES

- [1] P. Stott, "How climate change affects extreme weather events," *Science*, vol. 352, no. 6293, 2016.
- [2] W. A. Robinson, "Climate change and extreme weather: A review focusing on the continental united states," *JA&WMA*, 2021.
- [3] C. Parmesan *et al.*, "Impacts of extreme weather and climate on terrestrial biota," *Bulletin of the American Meteorological Society*, 2000.
- [4] K. L. Ebi *et al.*, "Extreme weather and climate change: population health and health system implications," *Annu. Rev. Public Health*, vol. 42, 2021.
- [5] K. V. Gough *et al.*, "Vulnerability to extreme weather events in cities: implications for infrastructure and livelihoods," *JBA*, 2019.
- [6] G. Camps-Valls *et al.*, "AI for modeling and understanding extreme weather and climate events," *Nature Communications*, vol. 16, 2025.
- [7] A. DiVenti *et al.*, "Nasa's safety, reliability, and mission assurance digital future," in *RAMS*, 2023.
- [8] S. M. Lundberg *et al.*, "A unified approach to interpreting model predictions," in *NeurIPS*, 2017.
- [9] A. B. Smith, "2023: A historic year of u.s. billion-dollar weather and climate disasters," 2023.
- [10] NCEI, "Global Forecast System (GFS)," 2025.
- [11] IPCC, "Climate change 2023: Synthesis report. Contribution of working groups I, II and III to the sixth assessment report of the intergovernmental panel on climate change," 2023.
- [12] G. C. Budget, "Global carbon budget 2023," 2023.
- [13] D. I. Domeisen *et al.*, "Advances in the subseasonal prediction of extreme events: Relevant case studies across the globe," *BAMS*, 2022.
- [14] Y. Lyu *et al.*, "Improving subseasonal-to-seasonal prediction of summer extreme precipitation over southern china based on a deep learning method," *Geophysical Research Letters*, vol. 50, no. 24, 2023.
- [15] X. Liu *et al.*, "Classified early warning and forecast of severe convective weather based on LightGBM algorithm," *ACS*, 2021.
- [16] X. Xiao *et al.*, "Long-term forecast of heatwave incidents in China based on numerical weather prediction," *TAAC*, 2024.
- [17] A. Chattopadhyay *et al.*, "Analog forecasting of extreme-causing weather patterns using deep learning," *JAMES*, vol. 12, no. 2, 2020.
- [18] A. Dikshit *et al.*, "An improved SPEI drought forecasting approach using the long short-term memory neural network," *JEM*, 2021.
- [19] W. Jiang *et al.*, "Transformer-based tropical cyclone track and intensity forecasting," *JWEIA*, vol. 238, 2023.
- [20] J. L. Coen *et al.*, "Wrf-fire: coupled weather–wildland fire modeling with the weather research and forecasting model," *JAMC*, vol. 52, 2013.
- [21] C. Rudin, "Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead," *Nature machine intelligence*, vol. 1, no. 5, pp. 206–215, 2019.
- [22] R. Yang *et al.*, "Interpretable machine learning for weather and climate prediction: A review," *Atmospheric Environment*, 2024.
- [23] E. D. Loken *et al.*, "Comparing and interpreting differently designed random forests for next-day severe weather hazard prediction," *Weather and Forecasting*, vol. 37, no. 6, pp. 871–899, 2022.
- [24] R. Cilli *et al.*, "Explainable AI detects wildfire occurrence in the Mediterranean countries of Southern Europe," *Scientific reports*, 2022.
- [25] A. Masrur, M. Yu *et al.*, "Capturing and interpreting wildfire spread dynamics: attention-based spatiotemporal models using ConvLSTM networks," *Ecological Informatics*, vol. 82, 2024.
- [26] M. T. Ribeiro, S. Singh, and C. Guestrin, "Why should i trust you?" explaining the predictions of any classifier," in *ACM SIGKDD*, 2016.
- [27] M. Ronco, J. M. Tárraga *et al.*, "Exploring interactions between socioeconomic context and natural hazards on human population displacement," *Nature Communications*, vol. 14, no. 1, 2023.
- [28] J. T. Trok, E. A. Barnes *et al.*, "Machine learning-based extreme event attribution," *Science Advances*, vol. 10, no. 34, 2024.
- [29] J. Wei, A. Bora, V. Oommen, C. Dong *et al.*, "XAI4Extremes: An interpretable ML framework for understanding extreme-weather precursors under climate change," *arXiv*, 2025.
- [30] G. Camps-Valls *et al.*, "AI for extreme event modeling and understanding: Methodologies and challenges," *arXiv*, 2024.
- [31] L. Peng, L. Gao, F. Hong, and J. Sun, "Evaluating pavement deterioration rates due to flooding events using explainable ai," *Buildings*, 2025.
- [32] A. Abdollahi and B. Pradhan, "XAI for interpreting the contributing factors feed into the wildfire susceptibility prediction model," *Science of the Total Environment*, vol. 879, p. 163004, 2023.
- [33] B. Liao, T. Zhou *et al.*, "Tackling the wildfire prediction challenge: An XAI model combining XGBoost with SHAP for enhanced interpretability and accuracy," *Forests*, vol. 16, no. 4, 2025.
- [34] G. R. Herman *et al.*, "Dendrology" in numerical weather prediction: What random forests and logistic regression tell us about forecasting extreme precipitation," *Monthly Weather Review*, 2018.
- [35] S. Mukherjee *et al.*, "Compound drought and heatwaves at a global scale: The role of natural climate variability-associated synoptic patterns and land-surface energy budget anomalies," *JGR: Atmospheres*, 2020.
- [36] P. Amoatey *et al.*, "Evaluating the association between heatwave vulnerability index and related deaths in Australia," *EIA Review*, 2025.
- [37] D. Fan *et al.*, "Explainable AI integrated feature engineering for wildfire prediction," *arXiv*, 2024.
- [38] H. S. Andrianarivony and M. A. Akhloufi, "Machine learning and deep learning for wildfire spread prediction: A review," *Fire*, vol. 7, 2024.
- [39] O. J. Pellicer-Valero *et al.*, "Explainable earth surface forecasting under extreme events," *arXiv*, 2024.
- [40] Y. Liu *et al.*, "Application of deep convolutional neural networks for detecting extreme weather in climate datasets," *arXiv*, 2016.
- [41] M. Marjani, M. Mahdianpari *et al.*, "Application of XAI in predicting wildfire spread: An ASPP-enabled CNN approach," *IEEE GRSL*, 2024.
- [42] W. Huang, "Extreme precipitation forecasting using attention augmented convolutions," *arXiv preprint arXiv:2201.13408*, 2022.
- [43] I. Prapas *et al.*, "Televit: Teleconnection-driven transformers improve subseasonal to seasonal wildfire forecasting," in *ICCV*, 2023.
- [44] F. Shafiq *et al.*, "Extreme heat prediction through deep learning and XAI," *PloS one*, vol. 20, no. 3, 2025.
- [45] S. Liu *et al.*, "Evaluation of tropical cyclone disaster loss using machine learning algorithms with an XAI approach," *Sustainability*, 2023.
- [46] H. Zhang *et al.*, "Using XAI and transfer learning to understand and predict the maintenance of Atlantic blocking with limited observational data," *JGR: Machine Learning and Computation*, 2024.
- [47] P. Gibson *et al.*, "Training ML models on climate model output yields skillful interpretable seasonal precipitation forecasts," *CEE*, 2021.
- [48] C. C. Ibeabuchi, "Uncertainty in machine learning feature importance for climate science: a comparative analysis of SHAP, PDP, and gain-based methods," *Theoretical and Applied Climatology*, vol. 156, 2025.
- [49] M. J. Molina *et al.*, "A benchmark to test generalization capabilities of deep learning methods to classify severe convective storms in a changing climate," *Earth and Space Science*, vol. 8, no. 9, 2021.
- [50] N. J. Leach, A. Weisheimer *et al.*, "Forecast-based attribution of a winter heatwave within the limit of predictability," *PNAS*, vol. 118, 2021.
- [51] X. Chen *et al.*, "Counterfactual analysis of extreme events in urban flooding scenarios," *Journal of Hydrology: Regional Studies*, 2025.
- [52] M. P. Thompson and J. F. Carriger, "Avoided wildfire impact modeling with counterfactual probabilistic analysis," *FFGC*, vol. 6, 2023.
- [53] L. Hoffman *et al.*, "Evaluating the trustworthiness of XAI methods applied to regression predictions of Arctic sea-ice motion," *AIES*, 2025.
- [54] N. Fraehr, Q. J. Wang, W. Wu, and R. Nathan, "Assessment of surrogate models for flood inundation: The physics-guided LSG model vs. state-of-the-art machine learning models," *Water Research*, vol. 252, 2024.
- [55] P. L. Bommer *et al.*, "Finding the right XAI method—a guide for the evaluation and ranking of XAI methods in climate science," *AIES*, 2024.
- [56] Y. Zhou *et al.*, "Comparative and interpretative analysis of CNN and transformer models in predicting wildfire spread using remote sensing data," *JGR: Machine Learning and Computation*, vol. 2, no. 2, 2025.
- [57] L. Chen *et al.*, "A machine learning model that outperforms conventional global subseasonal forecast models," *Nature Communications*, 2024.
- [58] M. Higa *et al.*, "Domain knowledge integration into deep learning for typhoon intensity classification," *Scientific reports*, vol. 11, 2021.
- [59] R. C. Staudemeyer and E. R. Morris, "Understanding LSTM—a tutorial into long short-term memory recurrent neural networks," *arXiv*, 2019.
- [60] A. Vaswani *et al.*, "Attention is all you need," *NeurIPS*, vol. 30, 2017.
- [61] M. Liu *et al.*, "Gated transformer networks for multivariate time series classification," *arXiv*, 2021.
- [62] L. Breiman, "Random forests," *Machine learning*, vol. 45, 2001.
- [63] S. Kondylatos *et al.*, "Mesogeos: A multi-purpose dataset for data-driven wildfire modeling in the Mediterranean," *NeurIPS*, vol. 36, 2023.
- [64] C. E. Yavas, C. Kadlec, J. Kim, and L. Chen, "California weather and fire prediction dataset (1984–2025) with engineered features," 2025.
- [65] J. Null and H. M. Mogil, "The weather and climate of California," *Weatherwise: The Power, the Beauty, the Excitement*, vol. 63, 2010.