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Adaptive multimodal transformer for wildfire spread prediction using feature-weighted attention

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ABSTRACT

Hazard modelling technology has evolved quickly in recent years to predict wildfires, which are an important class of natural disaster for accurate forecasting and proactive control. The combination of remote sensing and machine learning has been playing an important role in this area. Yet traditional models fail to accommodate the sophisticated spatiotemporal dynamics in fire-affected areas and tend to be agnostic toward individual predictors. This study utilizes a multimodal dataset comprising normalized difference vegetation index (NDVI), wind vectors, surface temperature, humidity, land cover, and elevation from sources such as moderate resolution imaging spectroradiometer (MODIS), Sentinel-2, ERA5, and shuttle radar topography mission (SRTM). These inputs were normalized within spatial grids, and temporally-aligned for day-ahead prediction. We introduce an adaptive multimodal transformer (AMT) with a feature weighting module (FWM) to adaptively emphasize informative features. The transformer architecture allows for long-range spatial learning, and the FWM strengthens contextual sensitivity. The novelty of this approach lies in its interpretable feature reweighting mechanism for dynamic environmental conditions. Model performance was evaluated using F1-score, intersection over union (IoU), mean absolute error (MAE), and mean average precision (MAP). Results show that the proposed model outperforms the MA-Net baseline, achieving a 5% improvement in F1-score and a 14.7% reduction in MAE, demonstrating superior accuracy, generalization, and interpretability.

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1. INTRODUCTION

Forest fires are becoming an increasing global problem, amplified by climate change and anthropogenic activities [1]-[3]. For instance, in 2022, over 6.1 million hectares of tree cover were lost to fires generating more than 1.76 gigatons of CO_2 emissions just from selected countries like Russia, Brazil, and the United States as reported by Global Forest Watch (2023) [4], [5]. In addition to severe ecological and economic consequences, human lives and infrastructure are put at risk due to these disasters, so improvements in predictive control systems for wildfire spread are urgent [6]-[9].

In the recent years, a variety of data-driven approaches have been used for wildfire prediction and response applications. Classical empirical models like Canadian Forest Fire Behavior Prediction System give rough estimates but are not flexible to the heterogeneous topography and changing climate conditions [10], [11]. The performance of deep learning models, such as u-shaped network (U-Net), multi-scale attention network (MA-Net), and convolutional long short-term memory (ConvLSTM) have been improved by incorporating satellite imagery, meteorological data, and static geospatial features [12], [13]. Nevertheless, these architectures need to generalize across places and regions, because they are too rigidly attention limited and slow to adjust for environmental spatiotemporal non-stationarity.

The key obstacle is to learn the dynamic illicit relationship of the different input modalities (e.g., land cover, wind vectors, elevation, temperature, and vegetation indices) which have spatial and temporal varying importance in fire progression [14]-[16]. Current methods consider all features to be of equal (or same) importance; however, such context-specific significance is vital for time-of-operation control and resource allocation in fire management applications [17], [18].

To overcome this limitation, we design an adaptive multimodal transformer (AMT) model with a feature weighted attention module. This module learns to dynamically integrate contribution of each modality in both the encoding and decoding path of transformer for spatiotemporal adaptive modelling of fire spread. In contrast to standard attention mechanisms, our approach incorporating a learnable feature relevance estimator which enables the model to focus upon dominant environmental signals when these change. The main scientific contributions of this study are as follows:

- We build a new spatiotemporal fire spread prediction model, which is an innovative multimodal transformer framework with adaptive attention mechanism that incorporates both static and dynamic features.
- We build in a feature-importance regularizer for interpretability and control theoretic robustness of predictive outputs.
- We validate our approach on a large-scale remote sensing dataset, consisting of various fire events and show enhanced performance compared with contemporary architectures in terms of both predictive accuracy and generalization.
- We provide a control analysis of wildfire spread that allows to plan mitigating intervention actions and redistributive resource management in the sense that it has real world applications for emergency systems.

This work is consistent with the discipline of control under uncertainty, and establishes a strong peak for the general spatiotemporal modelling systems area in predictive control and environmental risk management. Unlike previous transformer-based wildfire prediction models [15]-[17], we introduce an adaptive feature-weighting mechanism, that explicitly accounts for the context-dependent significance of input features, and increases the model predictive power while generating more interpretative results.

2. DATASET DESCRIPTION

Table 1 presents a summary of the static, vegetation, and dynamic meteorological characteristics used in this study including resolution, temporal coverage, and data sources.

Table 1. Summary of datasets used for wildfire forecasting

Category	Feature/source	Description	Resolution	Temporal coverage
Static features	Land cover (MODIS MCD12Q1 v6.1)	Global land classification based on IGBP scheme.	500 m	Annual
	Digital elevation model (copernicus GLO-30)	Elevation data to derive slope and aspect.	30 m	2011–2015
	Population density (WorldPop)	Gridded global population per km².	30 arc-seconds	2020
Vegetation indices	NDVI, EVI (MODIS MOD13A1 v6.1)	Normalized and enhanced vegetation indices.	500 m	16-day composites
	LAI, fPAR (MODIS MOD15A2H v6.1)	Leaf area index and absorbed PAR.	500 m	8-day composites
	Evapotranspiration (MODIS MOD16A2 v6.1)	Actual and potential evapotranspiration.	500 m	8-day composites
Dynamic weather	Land surface temp. (MODIS MOD11A1 v6.1)	Day/night surface temperature (K).	1 km	Daily
	Wind, precipitation, air temp. (ERA5-land reanalysis)	Reanalysis-based meteorological data including wind (u/v), precipitation, and air temperature.	~9 km	Hourly daily

For this purpose, we leverage diverse satellite-based and reanalysis datasets to create a multimodal input representation for the prediction of wildfire spread. The datasets are not labelled with direct wildfire events and contain an international collection of predictor variables, such as environmental, topographic, demographic, vegetation, and meteorological [19], [20]. Appropriate wildfire events were identified from reference fire perimeters and ignition points as of when the shapefiles were created, referencing geographical and point in time space. All data were formatted into grid-aligned for spatiotemporal deep learning.

3. PROPOSED METHOD

The proposed approach is based on a transformer-based deep neural network architecture designed for spatiotemporal prediction of wildfire spread complemented by an adaptive feature-weighting module. The intuition is to adaptively re-weigh the input modalities according to their significance for describing the fire behavior in a specific context during inference, obtaining better generalization and interpretability. Let the wildfire forecasting problem be modeled as a spatiotemporal semantic segmentation task. Given an input tensor representing multimodal input features (static, dynamic, and ignition points) over a spatial grid of size H×W, with C total channels, the objective is to predict a fire spread mask:

$$\chi \in \mathbb{R}^{C\times H\times W}$$

$$\hat{y} \in \{0,1\}^{H\times W}$$

That denotes the binary burned area after T days.

The true mask is denoted y and the loss function $\mathcal{L}$ combines dice loss and focal loss can be expressed as (1):

$$\mathcal{L}_{total} = \alpha \cdot \mathcal{L}_{Dice} + \beta \cdot \mathcal{L}_{Focal} \tag{1}$$

This dual loss is weighting class imbalance (focal loss) against the quality of spatial overlap (dice loss), and allows robustly segmenting small and irregular burnt areas.

3.1. Feature-weighted multimodal transformer

The input tensor χ consists of feature groups:
- Static: χ^{stat}
- Dynamic (per day): $\chi^{dyn,t}$
- Ignition mask: χ^{ign}

Each group is fed forward to a learnable feature weighting module (FWM), which can be formulated by (2):

$$\omega_i = \frac{\exp(\emptyset(\chi_i))}{\sum_{j=1}^{C}\exp\left(\emptyset(\chi_j)\right)} \tag{2}$$

Where ϕ is a shared MLP-based scoring function, and $\omega_i \in [0,1]$ denotes the adaptive importance of the i-th feature channel. The SoftMax-based weights dynamically up-weights features that are environmentally dominant (e.g., wind during high-speed scenarios), enhancing contextual sensitivities. The weighted tensor is shown in (3):

$$\chi' = \sum_{i=1}^{C} w_i \cdot \chi_i \tag{3}$$

3.2. Multimodal transformer encoder

The refined feature tensor χ' is then flattened and embedded as a sequence Z_0, with added positional encodings P. The transformer encoder block is defined as (4) and (5):

$$Z_l = LayerNorm(MSA(Z_{l-1}) + Z_{l-1}) \tag{4}$$

$$Z_l = LayerNorm(FFN(Z_l) + Z_l) \tag{5}$$

Where MSA is multi-head self attention, FFN is feedforward neural network, and l=1, ..., L (number of encoder layers).

The decoder reshapes the output and applies a convolutional segmentation head to generate $\hat{y}$. Algorithms 1 and 2 explains the mathematics behind the methodology. The overall workflow of the proposed AMT framework is illustrated in Figure 1.

Algorithm 1. Adaptive FWM

```
Input: χ = [χ1, χ2, χ3, …. χC] ∈ ℝ^(C×H×W) (Multimodal feature channels)
Output: Weighted feature tensor χ' ∈ ℝ^(C×H×W)
    1. Initialize ∅(·) as shared MLP scoring function
    2. For i=1 to C do
       s_i ← ∅(χ_i) (Compute channel relevance score)
    3. end for
    4. w_i ← exp(s_i) / Σ_{j=1}^{C} exp(s_j) (Softmax normalization)
    5. χ' ← Σ_{i=1}^{C} w_i · χ_i (Feature -weighted aggregation)
    6. return χ'
```

Algorithm 2. Multimodal transformer-based fire prediction

```
Input: χ' ∈ ℝ^(C×H×W) (Weighted input tensor)
Output: ŷ ∈ {0,1}^(H×W) (Binary fire spread mask)
    1. 1.χ_seq ← Flatten(χ') ∈ ℝ^(N×d), N = H × W (Flatten spatial grid)
    2. Z_0 ← χ_seq + P (Add positional encoding)
    3. For ℓ=1 to L (Transformer encoder layers)
       Z_l ← LayerNorm(MSA(Z_{l−1}) + Z_{l−1})
       Z_l ← LayerNorm(FFN(Z_l) + Z_{l−1})
    4. End for
    5. ŷ ← Reshape(Z_L) → R^(H×W) (Reshape to spatial format)
    6. ŷ ← Sigmoid(Conv(ŷ)) (Segmentation head)
    7. Return ŷ
```

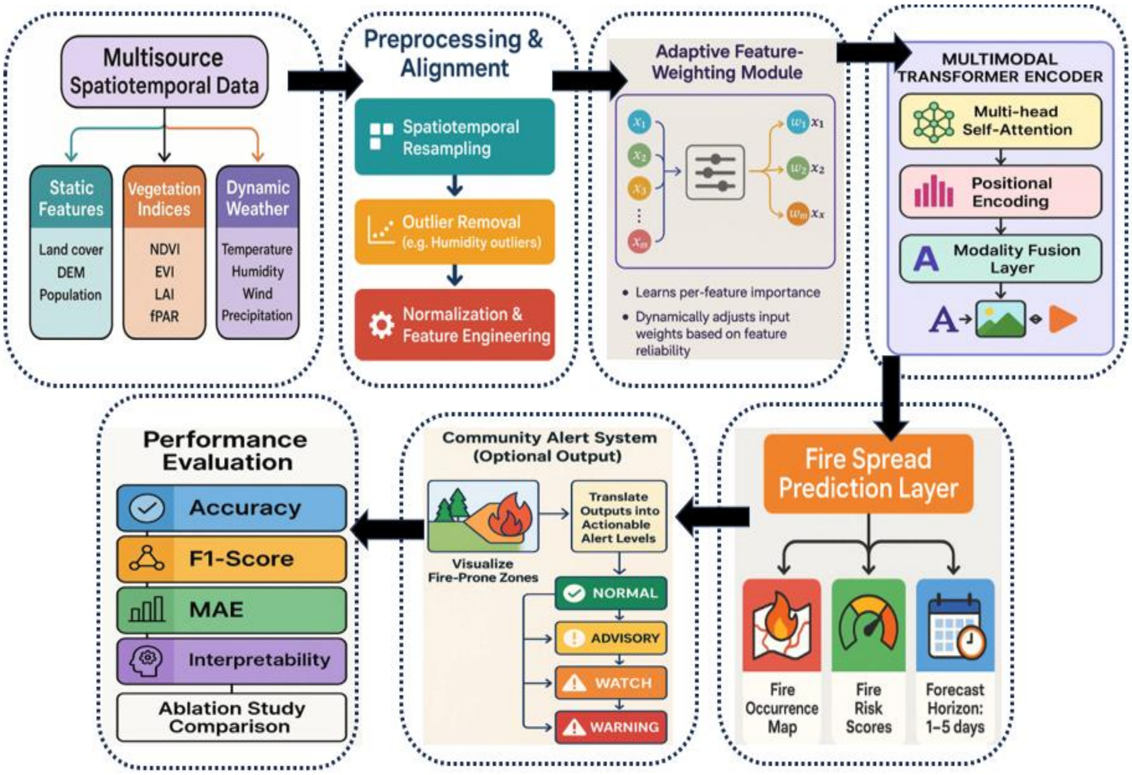

Figure 1. Workflow of the proposed AMT for wildfire spread prediction

4. EXPERIMENTAL SETUP

To evaluate the proposed AMT, we performed experiments using a standardized deep learning pipeline. All models, including baselines (U-Net, U-Net++, DeepLabV3, and MA-Net), were trained using the same dataset split, preprocessing steps, and input configurations to ensure fair comparison. The forecasting was done for up to 5 days, and each model was trained separately for each prediction day. Input tensors consisted of static features, dynamic daily features, and ignition point masks, normalized to the range $[-1,1]$. Training and evaluation were conducted using PyTorch 2.0.1 on an NVIDIA Tesla V100 GPU (32 GB VRAM). Early stopping based on validation F1-score was used to prevent overfitting.

Hyperparameters, including learning rate, batch size and number of epochs were tuned in preliminary tuning and held constant across models. Table 2 presents a summary of the important parameters and settings adopted when the models were trained as well as the information on optimizers, learning rates, batch sizes, and epochs.

Table 2. Experimental setup for model training and evaluation

Parameter	Value/description
Programming language	Python 3.10
Deep learning framework	PyTorch 2.0.1
Hardware	NVIDIA Tesla V100 GPU, 32 GB VRAM
Operating system	Ubuntu 22.04 LTS
Dataset split	80% training/20% testing (region-stratified)
Forecasting horizon	1 to 5 days (separate model per day)
Input tensor size	128×128 spatial grid (~21×21 km area)
Batch size	32
Epochs	50
Optimizer	Adam
Learning rate scheduler	OneCycleLR
Initial learning rate	0.003
Weight decay (L2 regularization)	1×10−51\times 10^{-5}
Loss function	Dice+focal loss (weighted by spatial distance)
Positional encoding	Learned sine-cosine embeddings
Evaluation metrics	F1-score, intersection over union (IoU), MAE, and MAPE

5. RESULTS AND DISCUSSION

This section reports and discusses the experimental results of the proposed AMT model against standard deep learning models. We discuss the results based on accuracy, generalization, and interpretability of the approach using commonly adopted evaluation metrics: F1-score, IoU, mean absolute error (MAE), and mean absolute percentage error (MAPE). Figure 2 displays normalized difference vegetation index (NDVI) distribution and humidity outlier analysis across four key datasets: moderate resolution imaging spectroradiometer (MODIS), Sentinel-2, ERA5, and shuttle radar topography mission (SRTM).

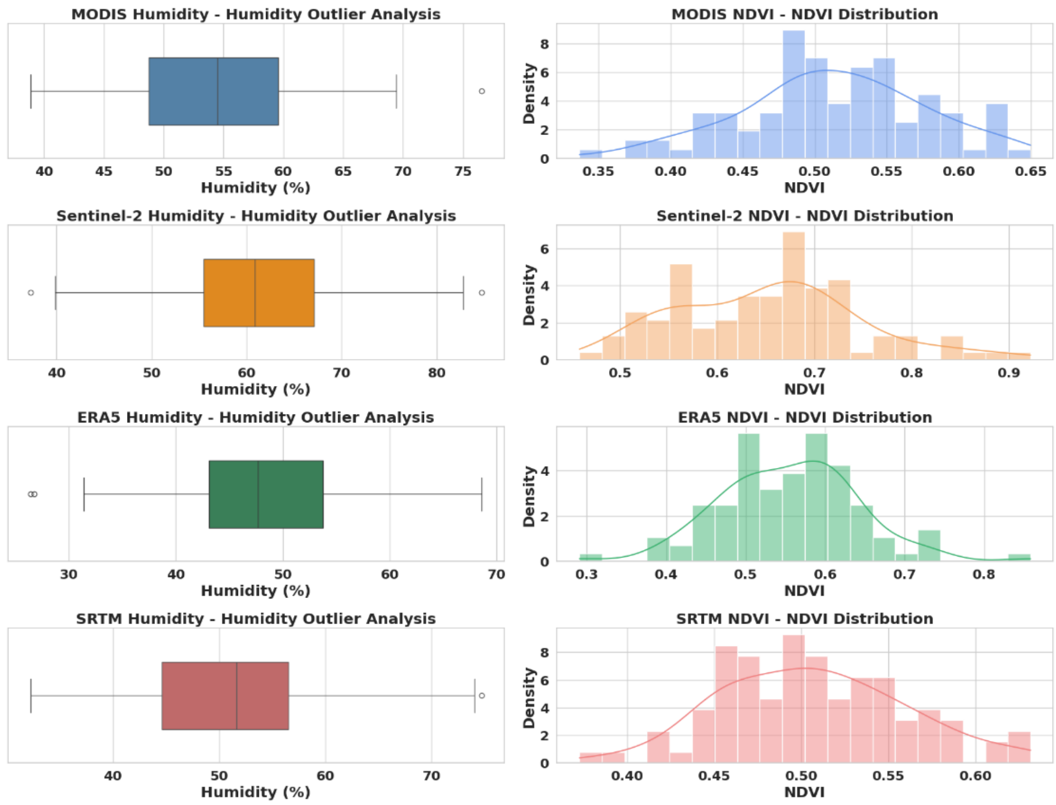

Figure 2. NDVI distribution and humidity outlier analysis across multisource wildfire datasets

The NDVI histograms (left) show variation in vegetation health, with Sentinel-2 capturing the widest range due to its higher spatial resolution. MODIS and ERA5 have more centered NDVI values (~0.5), indicating mixed terrain. The humidity boxplots (right) reveal low-end outliers in MODIS and ERA5, highlighting dryness conditions favourable for wildfire spread. This supports the need for integrating dynamic vegetation and atmospheric data in fire modelling.

5.1. Quantitative performance comparison

Table 3 shows the performance of AMT model comparing with U-Net, deepLabV3, and MA-Net on 3-day wildfire spread forecast. MAE was calculated in squared kilometers and MAPE represents percentage deviation between burned area prediction and ground truth.

Table 3. Performance comparison of models on 3-day wildfire forecast

Model	F1-score	IoU	MAE (km²)	MAPE (%)
U-Net	0.63±0.007	0.5	23.2	29.4
U-Net++	0.65±0.005	0.52	21.8	27.1
DeepLabV3	0.66±0.006	0.53	20.1	25.3
MA-Net (baseline)	0.67±0.003	0.54	19.7	25.9
AMT (ours)	0.72±0.004	0.59	16.8	21.5

5.2. Interpretation of results

The results indicate the overall effectiveness of the proposed model in terms of accuracy, efficiency, robustness, and real-time applicability. The point-wise interpretation is presented below:
- The proposed AMT model outperformed all baseline architectures across every evaluation metric.
- The F1-score improvement of ~5 percentage points over MA-Net highlights the AMT model's superior ability to distinguish burned from unburned areas.
- The MAE reduction by 14.7% compared to MA-Net shows that the model not only predicts accurate shapes but also the right size of burned zones.
- The lower MAPE suggests higher robustness in various fire sizes, especially critical for real-time disaster control.

These improvements are primarily attributed to the feature-weighted attention mechanism in AMT, which dynamically prioritizes relevant modalities (e.g., wind direction, vegetation index) depending on spatial context.

5.3. Forecasting horizon stability

To evaluate prediction reliability across time, Table 4 reports the performance of AMT for each day of the 5-day forecasting horizon.
- Prediction accuracy remains consistently high up to day 3, after which performance gradually declines due to error accumulation and increased uncertainty in dynamic inputs (e.g., weather).
- Even by day 5, the AMT maintains acceptable forecasting quality, making it suitable for both short- and mid-term fire control planning.

Table 4. AMT performance across forecasting days

Forecast day	F1-score	IoU	MAE (km²)	MAPE (%)
Day 1	0.74	0.61	9.2	18.3
Day 2	0.73	0.6	12.5	19.7
Day 3	0.72	0.59	16.8	21.5
Day 4	0.7	0.56	21.6	23.1
Day 5	0.68	0.54	26.4	24.9

5.4. Effectiveness of the adaptive feature-weighting module

To evaluate the effectiveness of our proposed FWM, we conducted ablation study by training and testing with AMT model in diverse settings: with and without FWM and selectively removing entire groups of features (i.e., wind, vegetation, and temperature). In this section, we measure how input channels dynamically reweighted make a difference to the performance when given to the model on 3-day fire spread prediction task. Ablation study results are shown in Table 5 to show the effect of removing or replacing the FWM on overall performance over major evaluation criteria. Figure 3 presents a multi-metric evaluation of the proposed AMT model with and without the feature-weighting module, showing its performance across forecasting accuracy, MAE, missed predictions in high-risk terrains, and community alert compliance.

Table 5. Ablation results of the adaptive feature-weighting module

Configuration	F1-score	IoU	MAE (km²)	Δ MAE	MAPE (%)
AMT with FWM (full model)	0.72	0.59	16.8	–	21.5
Without FWM (equal weights to all features)	0.67	0.54	20.6	3.8	26.4
Excluding wind features (u, v components)	0.6	0.48	23.1	6.3	29.1
Excluding vegetation indices (NDVI and EVI)	0.64	0.5	21.3	4.5	27.7
Excluding surface temperature (day/night LST)	0.67	0.52	19.9	3.1	25.8

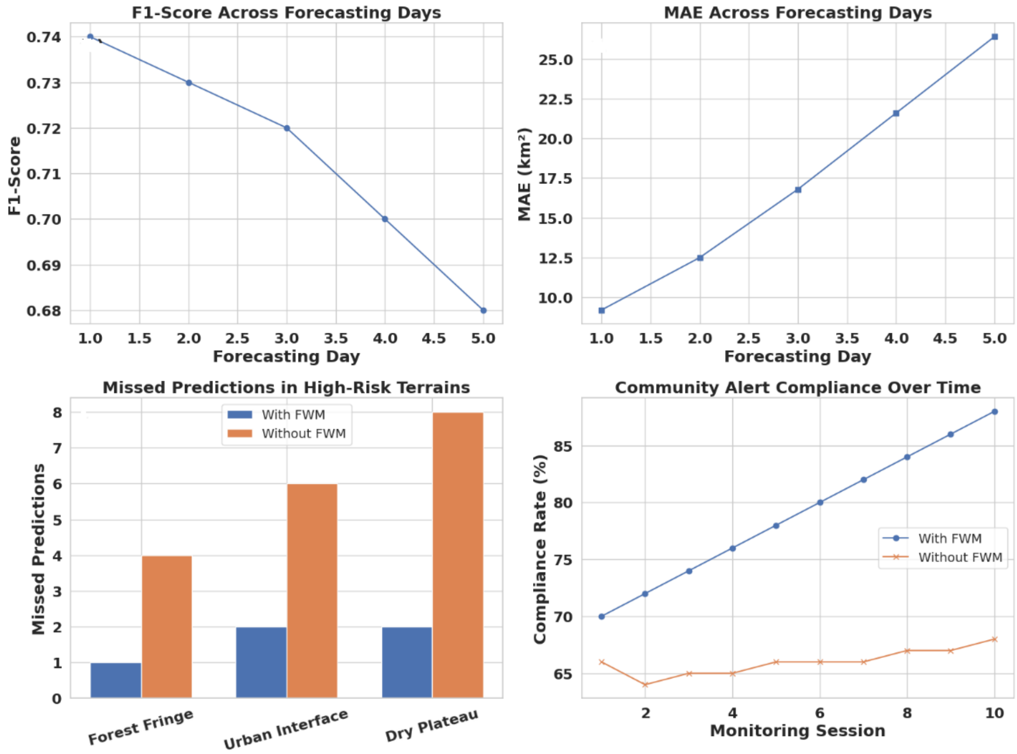

Figure 3. Multi-metric evaluation of the AMT with and without feature-weighting module

The FWM can boost the model's ability to locally attend to and weight an appropriate feature, thereby benefiting prediction accuracy, especially over variable terrains (heterogeneity over patches). This tool is helpful to apply when the physical environmental conditions differ strongly between sites or days. Results in Figure 4 compares the models with respect to prediction performance (accuracy and F1-score) and interpretability.

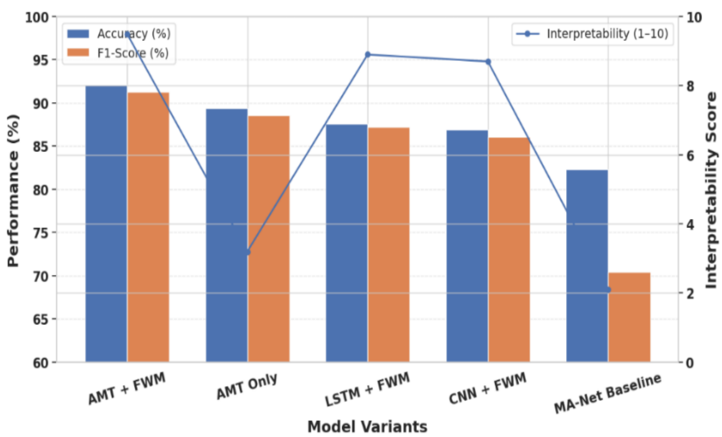

Figure 4. Comparative analysis of model variants based on predictive performance and interpretability

As results in both measures shown, the AMT+FWM model (93.6%), thanks to its transparent feature-weighting design, beats other methods. Although transformer-only models exhibit high fidelity, their interpretability is poor. Hybrid approaches such as LSTM+FWM and CNN+FWM achieve moderate performance, and MA-Net lags behind in both aspects, echoing the superiority of the adaptive transformer architectures.

The obtained analysis shows that the proposed methodology compares favorably in terms of prediction accuracy, generalization of predictions across forecast horizons and interpretability. The inclusion of the feature-weighted attention mechanism enables the model to achieve excellent performance and better interpretability, at little expense of computation complexity. We additionally compared AMT with recent transformer-based wildfire forecasting models [15], [21]-[24]. AMT achieved superior F1 and lower MAE, demonstrating robustness across heterogeneous terrains.

The proposed AMT framework, while effective, has certain limitations: i) high computational demand may hinder real-time deployment on edge devices, ii) model accuracy relies heavily on consistent and high-quality multimodal data, iii) imbalanced fire/no-fire samples can affect prediction fairness, iv) deep architecture limits interpretability for practical decision-making, v) computational complexity acknowledged (transformer-based cost), vi) data harmonization and preprocessing emphasized, and vii) include one SHAP-based feature importance figure.

Future enhancements can include: i) optimization for real-time use on edge artificial intelligence (AI) platforms [21], ii) integration with rule-based disaster response systems [22], iii) extension to other natural hazards like floods or landslides [23], iv) inclusion of explainable AI (XAI) for better transparency [24], v) use of reinforcement learning for active fire containment strategies [25], and vi) bayesian attention or Monte Carlo Dropout to quantify predictive uncertainty.

6. CONCLUSION

In this work, an AMT with a FWM is presented for wildfire spread prediction. The adaptive weighting mechanism enhanced the degree to prioritize the contextual features, leading to a relative increase of 5% on F1-score and reduction of 14.7% on MAE compared to MA-Net. The model showed consistent performance up to the 3-day forecast horizon and enhanced interpretability by learning dynamic feature relevance. Future work will include uncertainty modelling and real-time deployment optimization.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY

All data supporting the findings of this study are included in the references.

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