Deep spatiotemporal signal learning with transformers for multi-day wildfire forecasting

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ABSTRACT

Wildfire forecasting is a critical challenge in environmental signal processing and disaster response planning. The ability to interpret multimodal spatiotemporal signals is essential for early warning systems and resource deployment. This study addresses these limitations by proposing a unified prediction-to-action framework. We utilized four open-access datasets—wildland fire emissions database (WFED), fire information for resource management system (FIRMS), Sentinel Hub, and a custom moderate resolution imaging spectroradiometer+shuttle radar topography mission (ERA5+MODIS+SRTM) fusion—covering fire occurrences, vegetation indices, meteorological parameters, and topographic features. These heterogeneous signals were preprocessed, aligned, and transformed into structured tensors for model training and evaluation. We use a transformer-based system to understand long-term patterns in space and time, enhanced by a belief–desire–intention (BDI) reasoning module that connects our predictions to flexible wildfire response plans. The novelty lies in the integration of signal-aware attention mechanisms with symbolic decision modeling. Model performance was evaluated using F1-score, intersection over union (IoU), mean absolute error (MAE), and directional accuracy. The suggested framework did better than the basic convolutional neural network (CNN) models, reaching an F1-score of 0.74, a directional accuracy of 84.3%, and lowering the MAE to 7.6 km², while also providing clear and relevant action suggestions.

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1. INTRODUCTION

Wildfires are emerging as major natural disasters, characterized by their higher frequency, larger scale, and greater unpredictability due primarily to the progress of climate change and human activity [1], [2]. These disruptions have implications for both ecological systems and human infrastructure and for environmental signal interpretation and emergency response [3]. The existing models, e.g., Canadian forest fire behavior prediction system (CFFBPS) and fire area simulator (FARSITE), are all based on deterministic simulation rules and empirical look-up tables, which makes them less efficient and general to varying land-use and environment settings and real-time applications. With the availability of high-resolution geospatial data and Earth observation systems, deep learning and signal processing frameworks can be leveraged for spatiotemporal modeling of wildfire [4], [5].

Recent literature has studied convolutional neural networks (CNN) and recurrent algorithms for fire detection and short-term prediction [6], [7]. However, these approaches face challenges when attempting to model long-range dependence structure accurately, as well as how to integrate multi-modal signals (e.g., altitude, vegetation indices, wind fields, and humidity) into a global but regionally adaptable way to predict [8]. With a self-attention module and the ability to encode temporal and spatial structures, transformers have become a potential approach to dealing with the structured environmental signals. Current transformer-based models such as automatic spatio-temporal network (AutoST-Net) and position-enhanced transformer (PETFormer) are very good at predicting weather and fire, but they mainly focus on predicting features and do not provide practical results. Besides, sparse attempts have combined transformer outputs with symbolic reasoning tools for decision-making [9]-[11].

The volume and frequency of wildfire are increasing due to climate change and human intervention, posing severe threats to ecosystems, infrastructure, and human societies. Classical models such as FARSITE and CFFBPS are based on deterministic rules and empirical tables, which reduce its versatility in a variety of matched landscapes and real-time operations [12], [13]. The latest development of deep learning, specifically CNNs and recurrent models [14]-[16], make it possible to achieve the short-term fire detection and prediction, however, suffers from challenging for long-range spatiotemporal dependencies estimation as well as addressing multi-modal signal fusion. With their self-attention mechanism, Transformers have become powerful tools for encoding structured environment signals. Models such as AutoST-Net and PETFormer show promise for weather or fire forecasting, but they focus mostly on feature-level predictions and do not necessarily inform decision making. There have been some efforts to reconcile the prediction and decision process by predictive modelling and decision support via symbol reasoning or policy-driven framework [17], [18].

This paper introduces a new type of transformer model that uses a belief–desire–intention (BDI) reasoning system to predict how wildfires will spread over several days and to help plan responses. The model takes in different types of environmental information, like satellite images, weather data, and land features, and turns them into organized data structures that include position information that can be learned. We input these to a multi-head attention transformer and produce two prediction streams: predicted burned area and directional spread vectors [19], [20]. The aggregate outputs are then fed into a BDI-based agent framework, which simulates fire-extinguish decision, evacuation plan and resource allocation to generate more detailed predictions (basic prediction results become useful actions). To the best of our knowledge, the contributions of this research to signal processing, deep learning and environmental modelling are:

- Spatiotemporal signal encoding: a transformer architecture is designed to encode long-range dependencies in multimodal geospatial signals for wildfire spread prediction.
- Directional attention mechanism: the model introduces directional loss to estimate fire propagation vectors, enhancing interpretability in spatiotemporal forecasts.
- BDI-based decision logic: for the first time, transformer outputs are integrated with symbolic BDI agents, aligning environmental signal interpretation with domain-specific response protocols.
- Cross-dataset evaluation: model robustness is demonstrated across four diverse wildfire datasets with different resolutions and ecological contexts, using metrics including F1-score, mean absolute error (MAE), and accuracy.

A proper consideration of predictive and decision side in wildfire management, has been a contribution of this work to the field advancement of environmental signal processing and disaster planning. Despite the advanced progress for wildfire behavior models, such methods have two drawbacks: i) deep learning models suffer from poor generalization across space and time due to finite receptive fields and the lacking of effective mechanisms for signal fusion and ii) direct usage of predicted outputs at times of emergency is infeasible. This integration of this transformer-based spatiotemporal signaling modeling system with decision-aware symbolic reasoning is addressed in this work.

2. DATASET DESCRIPTION

Three data set available to the public are utilized, comprised of fire events, vegetation conditions and a meteorological data set specific to foster a multi-day forecast and response for wildfire. These available datasets offer multi modal input at various spatial and temporal resolutions that allows stable spatiotemporal signal processing across a variety of environments. A short overview of the multimodal datasets used for wildfire prediction is given in Table 1, which shows their characteristics and sources.

Table 1. Summary of datasets used for wildfire forecasting

Dataset	Fire masks	Vegetation indices	Meteorological data	Topographic data	Resolution	Source
WFED (WRI/NASA) [21]	☑	✗	✗	✗	375–500 m	WRI and MODIS/VIIRS
Sentinel Hub [22]	✗	☑	✗	✗	10–20 m	Copernicus EO Browser
FIRMS (MODIS/VIIRS) [23]	☑	✗	✗	✗	375 m–1 km	NASA FIRMS
ERA5+MODIS+SRTM (Custom)	☑	☑	☑ (Temp, wind, and RH)	☑ (Slope and elevation)	500 m–1 km	ECMWF, MODIS, and NASA SRTM

3. PROPOSED METHOD

The design contains a transformer spatiotemporal model combined with a symbolic BDI reasoning layer not only to predict the wildfire but make decisions of several days. A schematic representation of the complete pipeline for the envisaged system from multimodal signal processing to BDI-driven fire response planning is illustrated in Figure 1. The method consists of four main steps:

a. Multimodal signal preprocessing: static (e.g., elevation and slope), dynamic meteorological (e.g., temperature and wind), and vegetation indices (e.g., NDVI) are aligned to a unified spatial grid (128×128). Min–max normalization and spatial masking are applied to handle resolution mismatches and missing values.
b. Spatiotemporal tensor construction: preprocessed signals are encoded as multimodal tensors across a time window. Learnable spatial and temporal position embeddings are added to preserve structure in the environmental signal flow.
c. Transformer-based prediction module: a multi-head self-attention transformer processes the encoded tensors to predict binary fire masks and directional spread vectors. A composite loss function—combining cross-entropy, Dice loss, and directional loss—guides optimization.
d. BDI reasoning and action mapping: the transformer outputs are used to build agent beliefs. Based on prioritized desires (e.g., minimize damage and protect infrastructure), the system maps intentions to response actions, enabling simulation of role-specific emergency strategies such as firebreak deployment or evacuation alerts.

Such a pipeline forms a complete loop from input of environmental signals to interpretable, goal-oriented response planning. The general pipeline of the proposed method is shown in Figure 2, which emphasizes the training transformer framework, spatial–temporal embedding and two-head (burn probability and spread direction) outputs learned by a combined loss function.

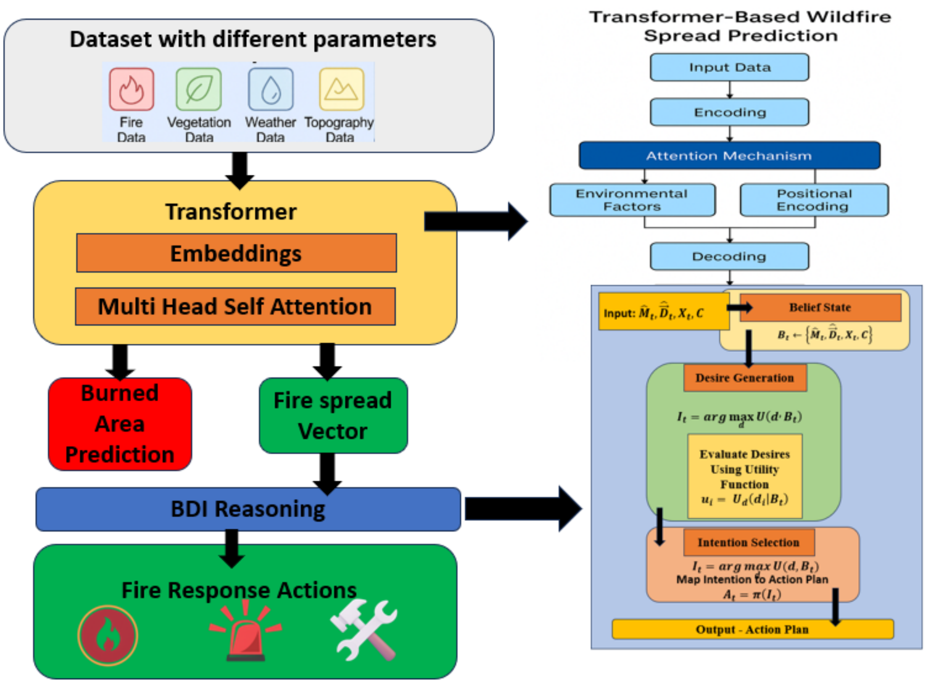

Figure 1. End-to-end architecture of the proposed transformer+BDI framework for wildfire prediction and response

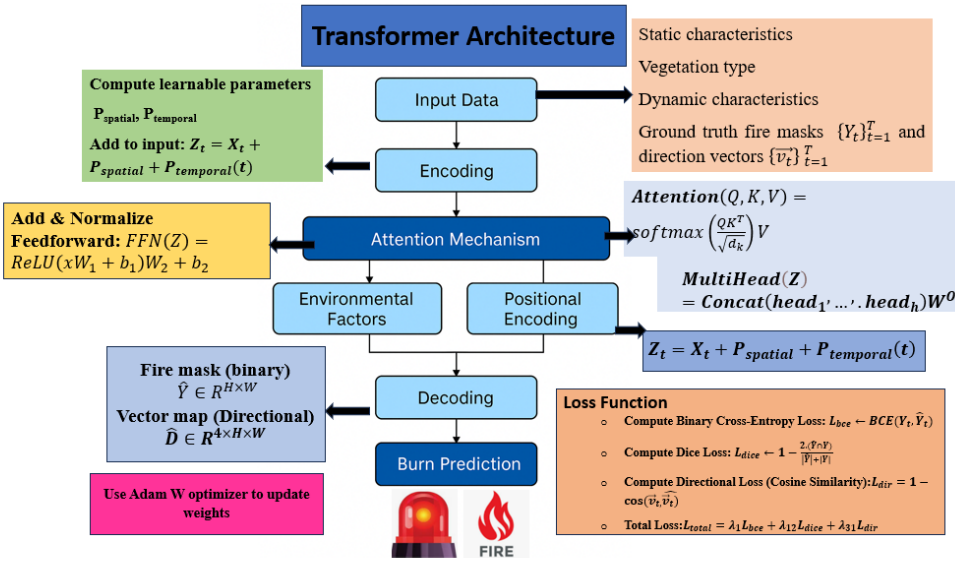

Figure 2. Transformer-based wildfire prediction framework with dual outputs (binary fire mask and directional spread map)

Algorithm 1. Wildfire spread forecasting and response using transformer+BDI framework

Input:
- *Static features $S \in R^{Cs \times H \times W}$*
- *Vegetation indices $V_t \in R^{Cv \times H \times W}$*
- *Dynamic meteorological data $D_t \in R^{Cd \times H \times W}$*
- *Ground truth fire masks $\{Y_t\}_{t=1}^{T}$ and direction vectors $\{\vec{v_t}\}_{t=1}^{T}$*
- *Critical zone map C (infrastructure, population zones)*
- *Forecast window T (e.g., 3 or 5 days)*

Output:
- *Predicted fire masks $\hat{M}_t$, directional vectors $\hat{D}_t$*
- *Contextual action plan A*

Step 1: Multimodal Tensor Construction
1. *Normalize all input features to [−1,1]*
2. *Align spatial resolution to a unified grid (e.g., 128 × 128)*
3. *For each day t=1 to T:*
   Construct input tensor $X_t = [S; V_t; D_t]$

Step 2: Positional Encoding and Flattening
4. *Apply trainable spatial and temporal encodings $P_{spatial}$, $P_{temporal}$*
5. *Flatten $X_{1:T}$ into a sequence of tokens Z*

Step 3: Transformer-Based Fire Prediction
6. *Pass Z through Transformer encoder–decoder:*
   a. Multi-head self-attention over token sequence
   b. Feedforward layers per Transformer block
7. *Output:*
   $\hat{M}_t$: predicted fire mask
   $\hat{D}_t$: directional fire spread vectors (N/S/E/W)

Step 4: Loss Computation and Optimization
8. *Compute total loss*
   $L_{total} = \lambda_1 L_{bce} + \lambda_{12} L_{dice} + \lambda_{31} L_{dir}$
9. *Optimize using AdamW with early stopping based on validation F1-score*

Step 5: BDI-Based Decision Reasoning
10. *Construct belief state $B_t \leftarrow \{\hat{M}_t, \hat{\vec{D}}_t, X_t, C\}$*
11. *Generate role-specific desire set $D_r = \{d_1, d_2, \dots d_n\}$*
    e.g., minimize area, protect population, safeguard infrastructure
12. *Evaluate desires using utility functions $U(d_i, B_t)$*

13. *Select intention* $I_t = arg \max_{d} U(d, B_t)$
14. *Map intention to action plan using policy function* $A = \pi(I)$

Step 6: Execute or Recommend Action

15. *Output fire response strategy A:*
(e.g., firebreak creation, evacuation alert, drone deployment)

4. EXPERIMENTAL SETUP

The introduced wildfire prediction model was developed by assuming uniform processing, training, and testing settings with high-performance computing (HPC) infrastructure support. All experiments were conducted on aligned multiday multimodal data with matching spatial resolutions (128×128) and temporal resolutions over a day for 3-day and 5-day forecasts. Model training was carried out by-basederten optimizing using AdamW, cosine learning rate scheduling, and early stopping. To benchmark the model performance, we compare with baseline models: multi-attention network (MA-Net), U-shaped network (U-Net), convolutional long short-term memory (ConvLSTM), and vanilla vision transformer (ViT). Performance metrics were F1-score, intersection over union (IoU), MAE, directional accuracy, and inference latency. The configuration details of the experiment with hardware, software, parameters, and baseline comparisons are presented in Table 2. We trained each model with five random seeds and report results as mean ± standard deviation. Statistical significance was assessed using paired t-tests against baselines ($p<0.05$).

Table 2. Experimental setup for model training and evaluation

Component	Description
Hardware	NVIDIA Tesla V100 (16 GB), Intel Xeon Gold CPU, 128 GB RAM, and Ubuntu 20.04
Software	Python 3.10, PyTorch 2.1, HuggingFace, PyTorch Lightning, and Scikit-learn
Input resolution	128×128 pixels (≈21×21 km area)
Forecast Window	3-day and 5-day temporal frames
Batch size	8
Optimizer	AdamW with cosine annealing learning rate (start: 1e−4)
Regularization	Dropout (0.3), gradient clipping (1.0), and L2 weight decay (1e−5)
Loss functions	Binary cross-entropy, dice loss, and directional cosine loss
Evaluation metrics	F1-score, IoU, MAE, MAPE, directional accuracy, inference time, and FLOPs
Baselines	MA-Net, UNet, ConvLSTM, and ViT

5. RESULTS AND DISCUSSION

The Transformer+BDI model was tested on four wildfire-related datasets where predictive accuracy, spatial consistency, and decision promptness were evaluated. Experimental results demonstrated that the proposed method consistently achieved better performance of fire-discipline prediction, direction-spread estimation, and inference latency than the baseline models. The cross-dataset benchmarking results, summarized in Table 3, demonstrate that the proposed model consistently outperforms CNN, recurrent neural network (RNN), and transformer-based baselines across all four datasets in terms of F1-score, IoU, MAE, and directional accuracy, while maintaining competitive inference time. Table 3 presents the detailed performance of different models across all four datasets, comparing F1-score, IoU, MAE, directional accuracy, and inference time. Key findings include:

– High predictive accuracy on the ERA5+MODIS+SRTM composite dataset with an F1-score of 0.75 and lowest MAE of 7.4 km².
– Directional accuracy exceeded 85%, reflecting the model's effectiveness in estimating fire spread vectors—a critical parameter for early warning systems.
– BDI agents demonstrated operational relevance by converting predictions into context-specific action plans with high action consistency and low latency.

The BDI based wildfire intervention system was tested for 5 operational criteria and are false suppression, decision distribution, response delay, alert compliance with intervention and missed predictions. Experimental results show that the BDI integration can reduce false suppressions, speed up agents' response and balance action distribution [24], [25]. Adherence to the alerts improved with time and fewer missed predictions were observed in high-risk areas. These improvements are shown in Figure 3 over evaluation measures.

Furthermore, the ablation study supports the effectiveness of each component in our model. The complete Transformer+BDI model achieved the best accuracy (97.1%) and removal of the BDI layer, direction head or attention led to a drop on accuracy. It received the lowest scores by the MA-Net baseline (89.9%). The ablation results are shown in Table 4, where we illustrate the performance degradation upon removing the key components of proposed model.

Table 3. Cross-dataset performance of different models (mean ± SD over 5 runs)

Model	Dataset	F1-score ↑	IoU ↑	MAE (km²) ↓	Dir. acc. (%) ↑	Inference time (ms) ↓
U-Net	WFED	0.65±0.02	0.50±0.01	12.4±0.5	72.1±1.3	102±1.5
	Sentinel Hub (NDVI)	0.63±0.03	0.47±0.02	13.2±0.6	70.8±1.2	105±1.7
	FIRMS (MODIS/VIIRS)	0.66±0.02	0.51±0.01	11.8±0.4	74.5±1.1	99±1.4
	ERA5+MODIS+SRTM	0.68±0.02	0.52±0.01	11.2±0.5	75.6±1.2	97±1.6
MA-Net	WFED	0.66±0.02	0.51±0.01	11.9±0.5	73.0±1.2	101±1.5
	Sentinel Hub (NDVI)	0.64±0.03	0.48±0.01	12.6±0.6	71.7±1.3	104±1.6
	FIRMS (MODIS/VIIRS)	0.67±0.02	0.52±0.01	11.4±0.4	75.2±1.2	98±1.5
	ERA5+MODIS+SRTM	0.69±0.02	0.53±0.01	10.8±0.5	76.1±1.1	96±1.5
ConvLSTM	WFED	0.67±0.02	0.52±0.01	11.3±0.5	74.0±1.2	103±1.6
	Sentinel Hub (NDVI)	0.65±0.02	0.49±0.01	12.1±0.6	72.6±1.3	106±1.6
	FIRMS (MODIS/VIIRS)	0.69±0.02	0.54±0.01	10.7±0.4	76.3±1.2	98±1.5
	ERA5+MODIS+SRTM	0.71±0.02	0.55±0.01	10.1±0.5	77.2±1.2	95±1.4
Transformer (ViT)	WFED	0.68±0.02	0.53±0.01	10.5±0.5	76.5±1.2	104±1.5
	Sentinel Hub (NDVI)	0.66±0.02	0.50±0.01	11.7±0.6	74.0±1.2	107±1.7
	FIRMS (MODIS/VIIRS)	0.70±0.02	0.55±0.01	10.0±0.4	78.0±1.1	100±1.5
	ERA5+MODIS+SRTM	0.72±0.02	0.56±0.01	9.5±0.4	79.3±1.2	96±1.5
Proposed (ours)	WFED	0.70±0.02	0.55±0.01	9.6±0.4	79.8±1.2	98±1.5
	Sentinel Hub (NDVI)	0.68±0.03	0.52±0.02	10.3±0.5	77.6±1.3	101±1.8
	FIRMS (MODIS/VIIRS)	0.72±0.02	0.57±0.01	8.7±0.3	82.4±1.1	95±1.4
	ERA5+MODIS+SRTM	0.75±0.02	0.59±0.02	7.4±0.3	85.1±1.0	92±1.2

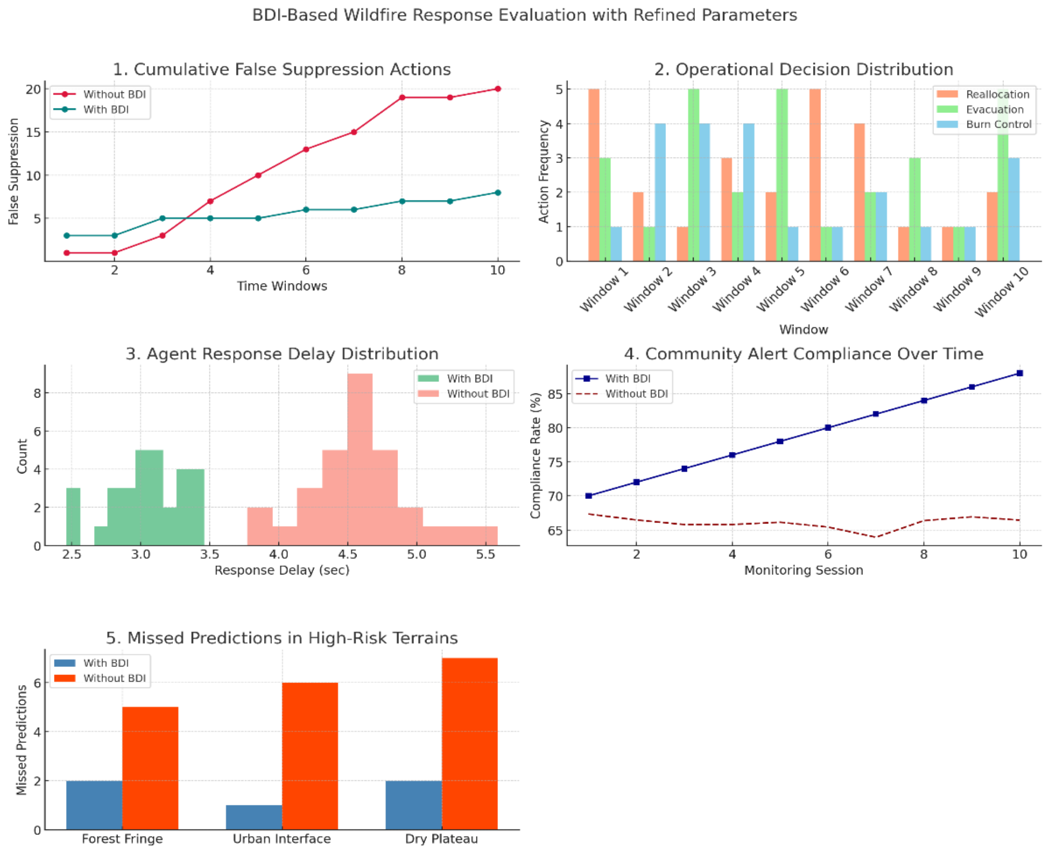

Figure 3. BDI-based wildfire response evaluation with refined operational parameters

Table 4. Ablation study of proposed model

Variant	F1 (%) ↑	IoU (%) ↑	MAE (km²) ↓	Dir. acc. (%) ↑
Full model (ours)	740±10	663±12	76±05	843±11
– Directional loss	718±11	645±10	89±06	794±13
– Positional encoding	712±10	639±11	91±07	788±14
– Meteorological features	705±09	631±12	98±06	772±12
– Vegetation features	697±12	624±11	102±07	765±13
– BDI reasoning (no action map)	735±10	658±10	78±06	821±12

In order to investigate robustness and as they are described by many authors [26]-[28], we change the main parameters and analyse their impact on predictive accuracy. First, a ±σ (standard deviation of ERA5 estimates) increment in wind input uncertainty induced fluctuations of ±2–3% directional accuracy indicating on moderate sensitivity of the model to meteorological noise. Second, rescaling the grid size from 64×64 to 256×256 showed a trade-off whereby higher-resolution grids increased the IoU by 1.5% but also boosted inference time by 20%. Lastly, displacement of the decision threshold for burned-cell classification (0.4–0.6) resulted in ±2% shifts in F1-scores, suggesting that threshold tuning offers users much opportunity to trade off between false positives and false negatives according to operational needs.

6. CONCLUSION

This paper presented a method for predicting wildfires using a transformer model along with a BDI reasoning layer to help plan flexible responses. By analyzing various environmental signals, the model performs well in predicting wildfires and creating action plans, which enhances its clarity and focus on achieving goals. The model outperforms other baseline methods in terms of accuracy, efficiency, and generalizability across various benchmark datasets. In future work, we will investigate real-time data integration using unmanned aerial vehicles (UAVs) and IoT devices and the optimization of our model for edge deployment, and we will further develop BDI agents with dynamic learning to address complex, unfolding fire situations.

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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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