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RESEARCH ARTICLE

Real-time forecast of high-resolution wildfire spread via Fast Cross-Scale Deep Learning

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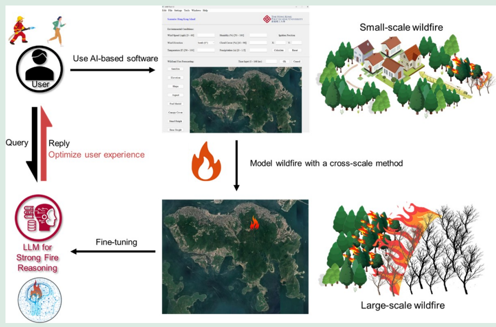
HIGHLIGHTS

- Develop a cross-scale AI framework for high-accuracy wildfire forecasting (25 m^2–20 km^2).
- Capture ignition and spread dynamics via multi-stage AI, overcoming detection challenges.
- Build a scalable dataset (240 fires, 8640 samples) and IWFTool for fast AI training.
- Bridge AI and wildfire management with efficient segmentation for real-time decision support.



ABSTRACT: The increasing frequency and severity of wildfires, particularly in the wildland-urban interface, underscores the urgent need for advanced real-time wildfire forecast models. This study develops a cross-scale deep-learning model for high-resolution wildfire emergency management that uses wildfires in Hong Kong Island, China as a demonstration. We simulate massive wildfire scenarios with a high spatial resolution of 5 m, based on historical fire records, and establish a numerical dataset of 240 fire cases (8640 samples of burnt area developing from a spot to vast landscape). Then, we introduce a cross-scale framework to achieve high-resolution wildfire spread forecast by avoiding the high-cost direct deep learning of high-resolution images. The framework forecasts the small-scale fire with 5-m resolution in the first 12 h and then smoothly transitions to 40-m resolution for forecasting the large-scale fire. The model is demonstrated to forecast the wildfire front and burning region crossing the spatial scale from 25 m^2 to 20 km^2 and achieve an overall accuracy of above 75% with a lead time ranging from 2h to 72 h. Finally, we develop a practical software, Intelligent Wildfire Forecast Tool (IWFTool), to integrate the cross-scale AI framework for supporting wildfire emergency response. The proposed smart framework enables the application of accurate, low-cost and fast-training AI tools for high-resolution wildfire forecasts and emergency responses.

KEYWORDS: Wildland fire, Artificial intelligence, Smart firefighting, Wildland-urban interface (WUI), Cross-scale model, Small object detection

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1 Introduction

Wildfires are a classic example of cross-scale natural hazards, shaped by complex interactions among multiple factors that govern their spread and behavior (Keys et al., 2019). These drivers can operate at multiple spatial and temporal scales, making wildfires a global concern due to their capacity to cause extensive damage across diverse landscapes (Moritz et al., 2014; McWethy et al., 2019). The scale of burnt areas and the intensity of wildfires vary significantly across different regions, drawing considerable attention from researchers, policymakers, and the public (Ermagun et al., 2025). In typical wildland-urban interface (WUI) areas (Mell et al., 2010), the rapid propagation of wildfires poses a significant threat to the safety of residents, often resulting in widespread panic and substantial socio-economic losses. In North America, especially the United States of America (Burke et al., 2021) and Canada (MacCarthy et al., 2024), and Oceania like Australia (Adedokun et al., 2024), for instance, wildfires often persist for extended periods, sometimes lasting several days or even weeks as shown in Fig.1(a). This prolonged duration is typically attributed to a combination of factors, including vast forested areas, favorable climatic conditions for fire spread, and, in some cases, limited immediate firefighting resources (Boroujeni et al., 2024) in the wildland urban interface (Chen et al., 2024).

In contrast, such prolonged wildfire events are relatively rare in East Asia (Li et al., 2024). In this region, wildfires and WUI fires at the city scale are more common, and their duration is generally limited to days (most less than one week) because of the strict full-suppression policy (Goldammer, 1999; Morgan, 2009; Hayes, 2021). The region's densely populated urban centers and developed infrastructure provide authorities with the capacity to rapidly mobilize firefighting resources, enabling the containment of wildfires before they escalate into larger, more catastrophic events. Furthermore, the forested areas in East Asia are generally smaller and more fragmented (Ma et al., 2023) compared to the vast, contiguous wilderness found in North America. However, the wildland-urban interface in East Asia presents unique challenges that complicate wildfire management. In cities and regions like China's Hong Kong, Singapore, and Sancheong of Republic of Korea, massive high-rise buildings and urban developments are often situated in close proximity to forested or vegetated zones, creating a complex and high-risk environment. Each wildfire incident in such WUI settings has the potential to pose significant threats to urban safety, with the risk of causing devastating hazards to both human populations and infrastructure (Manzello, 2020). This heightened

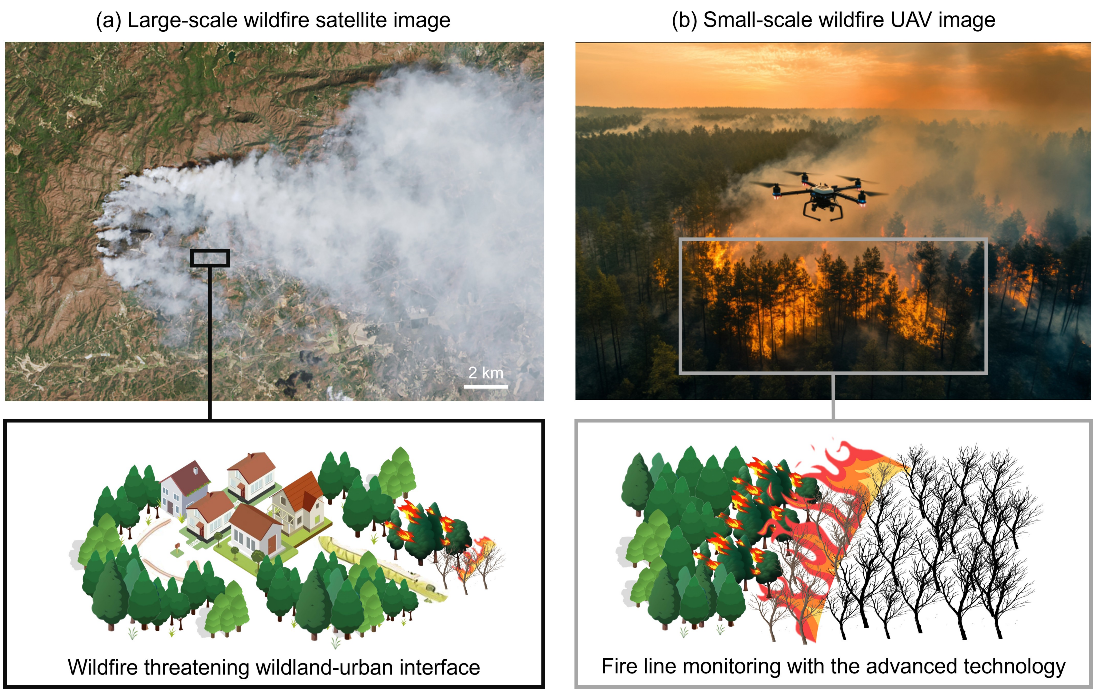

Fig. 1 (a) Large scale wildfire satellite image from NASA Earth Observatory in the western Carolinas and northeastern Georgia, USA, and (b) small-scale wildfire unmanned aerial vehicle monitoring to locate the wildfire spread.

vulnerability underscores the need for tailored strategies to address the distinct fire dynamics and risks associated with WUI regions, such as the applications of unmanned aerial vehicle (UAV) monitoring in Fig.1(b).

While traditional wildfire research has predominantly focused on classifying and predicting fire hazards through the development of fire risk indices (Oliveira et al., 2021; Bhowmik et al., 2023; Fu et al., 2025; Jiang et al., 2025), effective *in-situ* firefighting operations demand real-time, accurate fire information to optimize resource deployment and strategic decision-making (Martell, 2015). To address this need, various methodologies have been developed to predict the spread of wildfires with greater precision (Shadrin et al., 2024; Singh et al., 2024). These approaches, grounded in statistical, mathematical and physics frameworks, can be broadly categorized into three main types: statistical models, semi-physical semi-empirical models, and physics-based models (Sullivan, 2009a, 2009b, 2009c; Cruz et al., 2022). Statistical models leverage historical fire data and environmental variables to identify patterns and correlations, enabling probabilistic predictions of fire behavior. Semi-physical semi-empirical models combine fundamental physical principles with empirical observations, offering a balanced approach that integrates theoretical understanding with real-world data (Zhou et al., 2020). Physics-based models, on the other hand, rely on the fundamental laws of physics to simulate fire dynamics, providing a detailed and mechanistic understanding of fire spread under varying conditions but require a large amount of computational resources (Ronchi et al., 2019).

Each of these modeling approaches possesses distinct strengths and limitations, and their applicability is often contingent upon the specific context of the wildfire scenario, the availability of data, and the desired level of predictive accuracy. By integrating these methods, researchers and practitioners can enhance their capacity to forecast wildfire behavior in real-time, thereby improving the efficacy of firefighting efforts and mitigating risks to human life and property in WUI areas. Nevertheless, significant gaps persist between the operational needs of firefighting and the current state of wildfire research. Additionally, the specialized knowledge required to effectively utilize wildfire modeling tools often limits their practical application in the field.

In recent years, the advent of artificial intelligence (AI) has introduced transformative advancements in the field of wildfire spread modeling, establishing it as an emerging and highly promising area of research. Unlike traditional mathematical and statistical approaches, AI-based models leverage data-driven methodologies to identify and compute complex relationships among various environmental and fire-related parameters. By shifting from purely equation-based computations to pattern recognition within extensive datasets, AI models offer a novel paradigm for predicting wildfire behavior with enhanced precision and efficiency. Many researchers have integrated AI techniques with conventional wildfire models to improve the accuracy of fire spread predictions (Rios et al., 2016; Hodges and Lattimer, 2019). These hybrid approaches combine the strengths of physics-based or empirical models with the adaptive learning capabilities of AI, enabling more robust and reliable forecasts. Concurrently, advances in high-resolution satellite data have enhanced wildfire monitoring capabilities. Notably, Moun Space, in collaboration with the Earth Fire Alliance and Google researchers, has launched FireSat, a satellite system capable of capturing wildfire data at a 5-m resolution.

A key advantage of AI-based models is their ability to significantly reduce computational time, enabling real-time forecasting and making long-term wildfire simulations more practical. This efficiency enhances scalability, offering firefighting agencies and policy-makers critical tools for informed decision-making and risk mitigation. However, processing high-resolution imagery and large datasets with AI demands substantial computational resources during training, posing a challenge for implementation.

This study introduces a multi-stage modeling framework designed to capture the evolution of wildfires, with a particular emphasis on distinguishing between early-stage ignition dynamics and large-scale fire propagation behaviors. In the early stages of wildfires, AI learning small-ratio detailed information is challenging due to the limited pixel coverage of small-scale fires in satellite or aerial images. This issue resembles the small object detection problem in computer vision (Bosquet et al., 2020; Liu et al., 2021). However, unlike conventional segmentation and object recognition tasks, it requires specialized techniques to accurately characterize nascent wildfires.

By incorporating cross-scale segmentation, the proposed methodology effectively addresses the complexities of wildfire spread across different spatial and temporal scales. This approach not only simplifies the modeling process but also allows researchers to focus on the core aspects of the study area, reducing unnecessary computational and analytical efforts on peripheral regions. The multi-stage framework demonstrates considerable potential for advancing wildfire management practices. Specifically, it enables the generation of rapid, high-resolution fire spread forecasts, which are critical for real-time decision-making and resource allocation. Furthermore, the integration of this methodology into cloud-based wildfire monitoring systems offers a scalable and accessible solution for firefighting agencies and emergency responders.

2 Methodology

2.1 Study area

Hong Kong is a densely populated modern metropolis with over 4000 skyscrapers, yet approximately 70% of its land area is covered by woodland, shrubland, and wetland. This unique combination makes it a wildland-urban interface, where the threat of wildfires is a persistent concern. According to data from the Hong Kong Fire Services Department, an average of 800 wildfires are reported annually from 2010 to 2020 (Chan et al., 2023; Chan and Coomes, 2024), and the accident distribution is visualized in Fig. 2(a). Likewise, Fig. 2(b) illustrates that over 80% of these wildfires are confined to a burning area of less than 1000 m^2 and are extinguished within 24 hours, largely due to the city's robust firefighting capabilities. However, some wildfires escalate, spreading to adjacent high-density urban areas, posing significant safety risks and contributing to severe air pollution.

Hong Kong Island, the second-largest island in Hong Kong, has been selected as the research area for this study. With a total area of 78.59 km^2 and a population of approximately 1188500 (by 2023), it represents a critical wildland-urban interface where urban development intersects with natural landscapes. Over 80% of the island area is covered by vegetation, making it particularly susceptible to wildfire risks. Historical wildfire incident data reveal that while the majority of fires are contained within 24 h, a small proportion may persist for up to 72 h. This heightened vulnerability highlights the necessity for tailored strategies to address the unique fire dynamics and risks in WUI regions. Given the island's high population density, there is an urgent need for high-resolution wildfire monitoring and forecasting systems that align with the demands of rapid firefighting response to safeguard both human lives and infrastructure.

2.2 Wildfire-spread database

To simulate wildfire spread dynamics, this study employs FARSITE (Finney, 1998), a computational modeling tool developed and extensively utilized by the U.S. Forest Service. FARSITE is recognized as a robust and reliable platform for simulating wildfire propagation processes and evaluating the spatial extent of burned areas. The software operates by solving the fundamental wildfire spread equations formulated by Rothermel (Rothermel, 1972) and Albini (Albini, 1985), which are grounded in the principles of fire behavior physics. These equations enable the prediction of two-dimensional fire perimeters by calculating the fastest local rate of fire spread and its directional components.

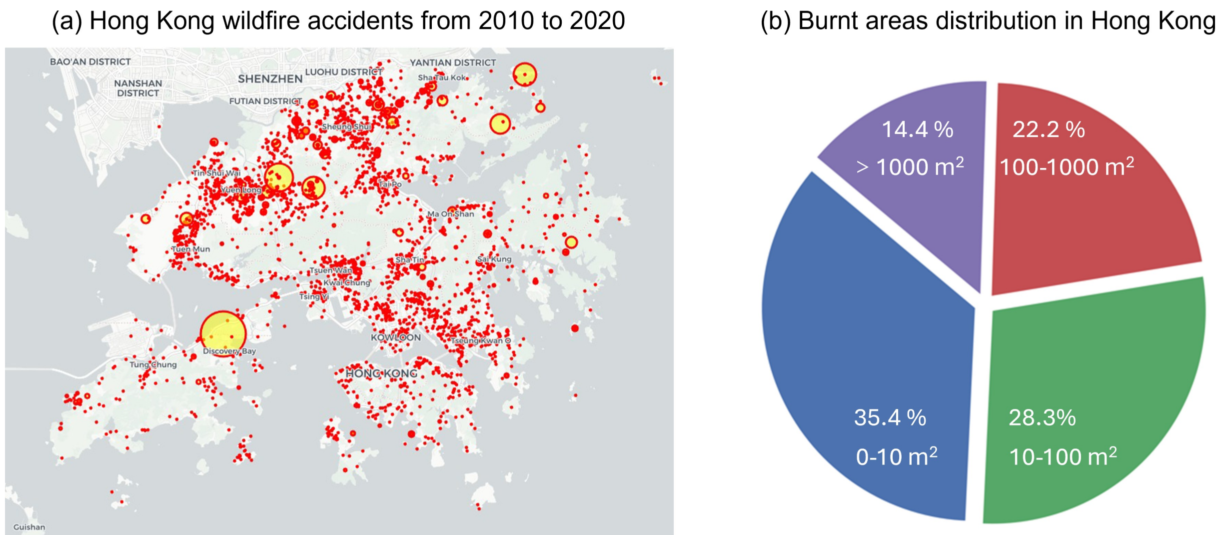

Fig. 2 (a) The distribution of Hong Kong wildfire accidents according to data provided by Hong Kong Fire Service Department, where the red circle is equivalent to the burnt area for demonstration, and (b) Hong Kong wildfire burnt area distribution by range, most of which are small-scale wildfire accidents and less than 1000 m^2.

$$R = \frac{I_R \xi (1 + \phi_w + \phi_s)}{\rho_b \epsilon Q_{ig}}, \tag{1}$$

where I_R is the reaction intensity, ξ is the moisture damping, ϕ_w is the wind, ϕ_s is the slope, ρ_b is the effective bulk density, ϵ is the effective heating and Q_{ig} is the heat of pre-ignition. As such, FARSITE provides a scientifically rigorous framework for modeling wildfire scenarios, making it well-suited for this investigation.

In this study, a series of numerical wildfire cases were generated using FARSITE to simulate potential fire spread patterns under varying environmental and ignition conditions. The operational modeling process incorporates a range of input parameters, which are critical for accurately representing wildfire behavior. Table 1 provides a detailed summary of the essential parameters used in the simulations. Among these, three key variables were prioritized due to their significant influence on fire dynamics: wind speed, wind direction, and ignition points. Wind speed and direction are particularly critical, because they directly affect the rate and direction of fire spread, while ignition points determine the spatial origin of wildfires.

To ensure comprehensive coverage of the study area, a diverse set of scenarios was constructed. The database comprises a total of 240 cases, systematically designed to account for variability in environmental and ignition conditions. Specifically, the scenarios include 4 distinct wind directions, 5 discrete wind speed values, and 12 strategically selected ignition points (see Fig. 3(a)). These ignition points were distributed across Hong Kong Island to represent potential fire origins within its densely vegetated areas. This approach ensures that the simulations capture a wide range of possible wildfire behaviors, thereby enhancing the robustness and applicability of the findings.

Table 1 Modeling properties used in the present study, where the data are from Hong Kong Lands Department and Observatory

Parameter	Value
Vegetative fuel	SH3 (143) (Scott and Burgan, 2005)
Elevation & Slope & Aspect	5-m resolution
Ambient Temperature	80 K
Relative Humidity	75%
Cloud Cover	60%
Stand Height	7.5 m
Canopy Base Height	1.5 m
Canopy Bulk Density	20%
Wind Speed	6, 12, 18, 24, 30 m/s
Wind Direction	North, South, East, West
Ignition Points	12 locations in Fig. 3

To accurately model wildfire behavior, we utilize high-resolution (5 m) satellite data for numerical simulations, given Hong Kong Island's limited spatial extent. At this resolution, each pixel corresponds to a 5 m × 5 m area, ensuring sufficient granularity for localized fire dynamics. Coarser resolutions (e.g., 50 m or 300 m) would inadequately represent the island's topography and fuel distribution and reduce the model's accuracy. As illustrated in Fig. 3(b), simulating the entire study area (3072 × 2304 pixels) would be computationally prohibitive, particularly for training complex AI models. The processing dataset size would exceed the capacity of our available hardware (NVIDIA Tesla P100 GPU with 16 GB memory).

To address this challenge, we propose a cross-scale

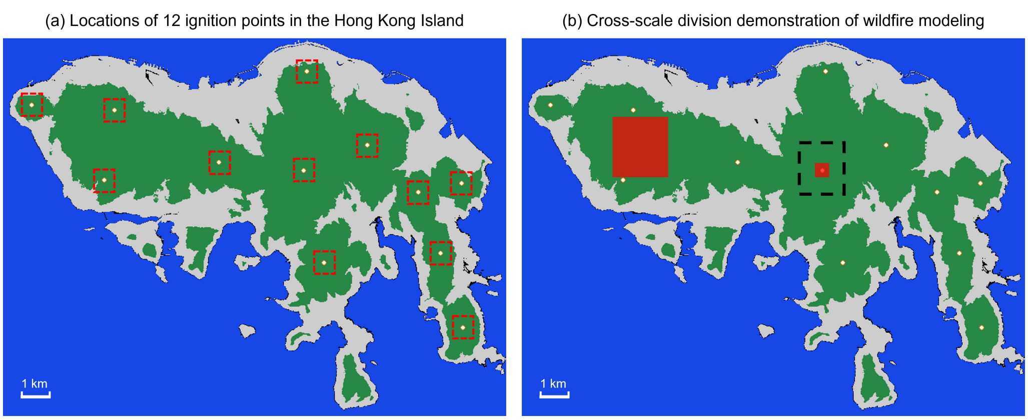

Fig. 3 The whole region of Hong Kong island is captured by an image of 3072 × 2304 pixels, and each pixel is 5 m × 5 m area. (a) Locations of the 12 ignition points in the fuel model and (b) cross-scale wildfire demonstration of wildfire modeling. Although the Hong Kong Island is the research area, different scales of wildfire burnt areas need different scales and resolutions to simulate fire spread.

division of the training area, optimizing computational efficiency without sacrificing accuracy. The methodological details of this approach are elaborated in subsequent sections. By leveraging FARSITE's computational capabilities and systematically varying key parameters, these simulations provide a detailed analysis of wildfire spread patterns on Hong Kong Island.

2.3 Cross-scale deep-learning framework

The primary objective of this study is to model cross-scale and high-resolution wildfire dynamics using a deep learning approach. Figure 4 illustrates the fundamental workflow of the proposed methodology. Wildfires can be categorized into two distinct phases based on their temporal and spatial scales: early-stage or small-scale wildfires, and large-scale wildfires. Each phase presents unique challenges and requires strategies for effective modeling and prediction.

For early-stage or small-scale wildfires shown in Fig. 4(a), which are characterized by a duration of less than 12 h or a burned area of fewer than 1000 m^2, high-resolution spatial data is critical for accurate forecasting. However, the limited number of burnt pixels in such scenarios poses a significant challenge for artificial intelligence training. Directly feeding high-resolution images with sparse burnt pixels into an AI model often results in inefficient computational resource utilization, as the small number of relevant pixels may not be effectively detected by the model's convolutional kernels. To address this issue, we propose an innovative approach that avoids resizing the original high-resolution images. Instead, the images are divided into thousands of overlapping blocks. This segmentation strategy ensures that the AI model can effectively detect and learn from the sparse burnt pixels while capturing the underlying wildfire spread patterns. The overlapping blocks also enhance the model's ability to generalize across different spatial contexts, thereby improving its training performance and predictive accuracy.

In contrast, for large-scale wildfires in Fig. 4(b), high-resolution imagery becomes computationally prohibitive due to the substantial data volume. Directly processing original high-resolution images in the AI

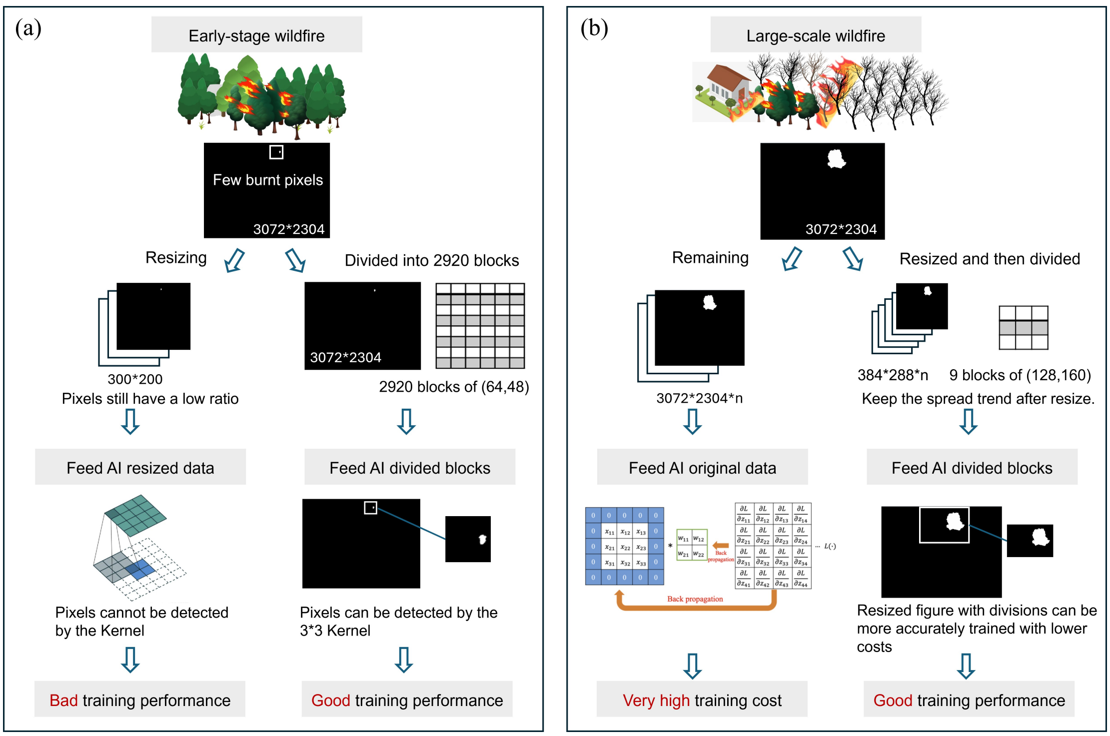

Fig. 4 Process of the methodology for cross-scale wildfire modelling, (a) for early-stage wildfire or small-scale wildfire, we choose to use high-resolution information sources to predict the wildfire spread, diving them into 2920 blocks. It solves the problem that the convolutional kernel cannot scan very few burnt area pixels, achieving a good training performance; and (b) for large-scale wildfire or small-scale wildfire, if we choose to use high-resolution information source as training input, the computational cost and time will increase greatly.

model leads to failure, as the computational requirements exceed available graphics memory of GPUs. To address this limitation and reduce the computational costs, we implement a resizing strategy that reduces image dimensions while retaining key wildfire spread characteristics. The resized images are subsequently partitioned into nine overlapping blocks. This method significantly alleviates computational demands during AI training while preserving the critical spatial information necessary for accurate wildfire propagation modeling. By optimizing input data complexity, the AI model can more effectively learn wildfire spread dynamics, facilitating faster and more scalable predictions.

The proposed methodology establishes a comprehensive database based on the division techniques described above. This database serves as the foundation for training the deep learning model, enabling it to effectively capture and predict wildfire behavior across different scales. To achieve cross-scale wildfire modeling, we employ the classical U-Net architecture (Long et al., 2015), a well-established convolutional neural network model renowned for its effectiveness in image segmentation tasks. The U-Net model is particularly suited for this study due to its unique structure, which combines convolutional down-sampling and up-sampling pathways to capture both local and global features within the input data. This dual-pathway design enables the model to effectively process high-resolution images while maintaining the spatial precision necessary for accurate wildfire spread prediction.

The U-Net architecture for two models (Figs. 5(a) and 5(b)) consist of several blocks, each comprising convolutional layers followed by down-sampling or up-sampling operations. In the down-sampling pathway, convolutional layers extract hierarchical features from the input images, progressively reducing their spatial dimensions while increasing the depth of the feature maps. This process allows the model to capture high-level patterns and contextual information related to wildfire behavior. Conversely, the up-sampling pathway utilizes transposed convolutional layers to reconstruct the spatial dimensions of the feature maps, enabling precise localization of burnt areas and wildfire spread boundaries. Skip connections between corresponding layers in the down-sampling and up-sampling pathways further enhance the model's performance by preserving fine-grained details that might otherwise be lost during the down-sampling process.

To optimize the model's efficiency, we adjusted the number of convolutional blocks based on the input and output sizes. For the early-stage wildfire detection model (Fig. 5(a)), we reduced the number of convolutional blocks to simplify the model's structure. This modification not only speeds up training but also helps prevent overfitting. In contrast, the large-scale wildfire model (Fig. 5(b)) employs more blocks, resulting in higher computational costs during training.

3 Results and discussion

We conducted a comparative analysis among Flammap, single-scale/high-resolution AI models, and our proposed cross-scale AI framework in Table 2. Flammap, which serves as the benchmark in this study, requires tens of minutes to simulate a single large-scale wildfire case, whereas the AI models complete predictions in seconds to tens of seconds. However, this computational efficiency comes at a cost: AI models require extensive pre-training and achieve slightly lower accuracy compared to the benchmark. Among the AI-based approaches, traditional single-scale and high-resolution models demand substantial computational resources and perform poorly in early-stage wildfire detection. In contrast, our proposed cross-scale AI framework delivers the fastest prediction latency, moderate training costs, and relatively high prediction accuracy.

3.1 Model evaluation

The evaluation of model performance is a fundamental component of deep learning applications, as it provides critical insights into the effectiveness and reliability of the developed models. A widely adopted approach for assessing model performance involves the use of loss functions, which quantify the discrepancy between predicted outputs and ground truth values during the training process. In this study, we utilize binary cross-entropy as the loss function, a well-established metric for evaluating binary classification tasks. Binary cross-entropy is particularly suitable for this work, as the wildfire spread modeling problem is framed as a binary classification task, where burnt areas are represented by the value 1 and unburnt areas by the value 0. This approach allows for a clear and interpretable assessment of the model's ability to distinguish between these two classes.

Initially, we considered using accuracy in Eq. (2) as the primary metric for evaluating the model's performance during validation. However, this approach proved inadequate due to the imbalanced nature of the

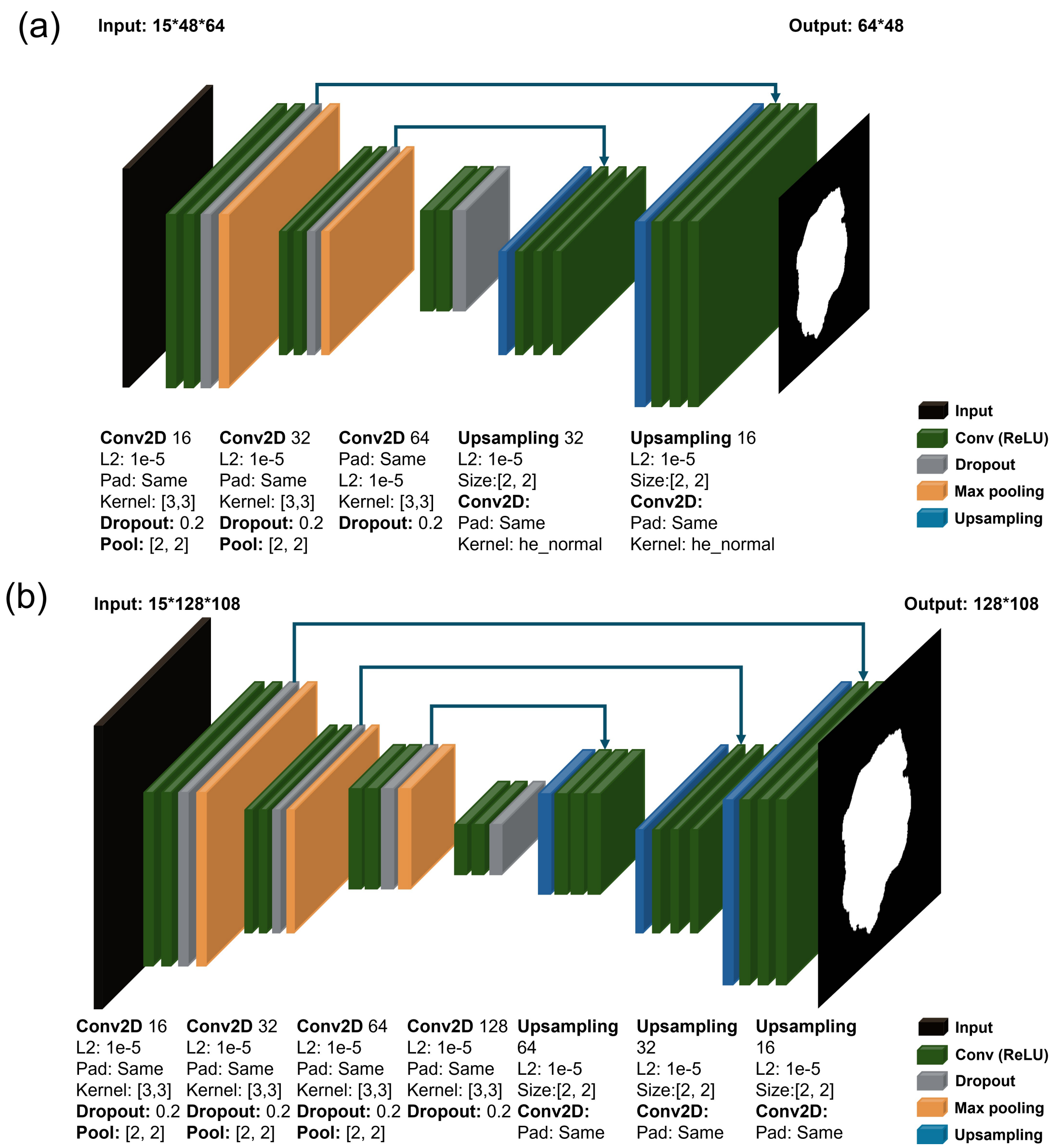

Fig. 5 The structure of U-Net model used in the AI training, (a) U-Net structure for early-stage wildfire and (b) U-Net structure for large-scale wildfire.

dataset. In wildfire spread modeling, the burnt areas (represented by value 1) typically constitute a very small proportion of the total area, resulting in an extreme class imbalance. This imbalance creates a scenario where the model can achieve high accuracy by predominantly predicting the majority class (unburnt areas), while failing to correctly identify the minority class (burnt areas). Such a model, despite its high accuracy, would be of limited practical utility, as its ability to detect critical areas of wildfire spread would be severely compromised.

To address this challenge, we adopted alternative evaluation metrics that are more robust to class imbalance. As illustrated in Table 3, the model's tendency to misclassify burnt areas (positive values) as unburnt areas (negative values) is a direct consequence of the dataset's extreme imbalance.

Metrics such as precision, recall, and the F1-score in Eqs. (3)–(5) provide a more nuanced assessment of the model's performance by focusing on its ability to correctly identify the minority class. Precision measures the proportion of correctly predicted burnt areas relative to all predicted burnt areas, while recall quantifies the proportion of actual burnt areas that the model successfully identifies. The F1-score, which is the harmonic means of precision and recall, offers a

Table 2 Training and Prediction cost for different framework

Features	Flammap	Single-scale & high-resolution	Cross-scale AI framework
Resolution (pixel size, duration)	3072 × 2304 (5 m × 5 m, 0–72 h)	3072 × 2304 (5 m × 5 m, 0–72 h)	48 × 64 (5 m × 5 m, 0–12 h) 128 × 160 (40 m × 40 m, 12–72 h)
Prediction delay	10^3 s (slow modeling)	10^2 s (slow rendering)	< 10 s (fast rendering)
Training time/cost	N/A	Super High	Moderate
Knowledge	Empirical	Single AI model	Two AI models
Accuracy	Benchmark	~50%	~75%

Table 3 Confusion matrix of prediction and truth

Confusion Matrix		Prediction	
		Positive	Negative
True	Positive	True Positive (TP)	False Negative (FN)
	Negative	False Positive (FP)	True Negative (TN)

balanced measure of the model's performance in the context of class imbalance.

$$\text{Accuracy} = \frac{\text{correct classifications}}{\text{total classifications}} = \frac{TP + TN}{TP + TN + FP + FN}, \tag{2}$$

$$\text{Recall} = \frac{\text{correctly classified actual positives}}{\text{all actual positives}} = \frac{TP}{TP + FN}, \tag{3}$$

$$\text{Precision} = \frac{\text{correctly classified actual positives}}{\text{everything classified as positives}} = \frac{TP}{TP + FP}, \tag{4}$$

$$\text{F1 score} = 2 \times \frac{\text{Precesion} \times \text{Recall}}{\text{Precesion} + \text{Recall}} = \frac{TP}{TP + FP}. \tag{5}$$

By shifting our focus from accuracy to more suitable evaluation metrics, we ensure a comprehensive assessment of both models' performance, particularly their capability to detect and predict critical wildfire spread patterns, as illustrated in Figs. 6(a) and 6(b). Given the inherent class imbalance in the dataset, we employ the F1-Score as the primary performance indicator. The early-stage wildfire model achieves an F1-Score of 0.65, while the large-scale wildfire model attains a higher score of 0.75, reflecting its improved ability to handle more extensive fire scenarios.

3.2 AI predicted result demonstration

To assess the performance of our wildfire spread prediction model, we analyzed two representative cases (Videos S1 and S2). The results indicate that the AI model successfully captures the overall wildfire spread dynamics. However, a notable limitation arises in Video S1, where a significant number of false positives emerge between the 6- and 10-h mark. This observation suggests that the model's robustness requires further validation, particularly due to the block division processing employed during training.

A detailed comparative analysis reveals that the AI-predicted burnt area tends to be slightly larger than the FlamMap benchmark. We hypothesize that this discrepancy stems from the relatively low proportion of burnt-area pixels in the input data. When the 3 × 3 convolutional kernel processes the full image, this class imbalance may introduce minor but systematic biases in the predictions.

For additional validation, we extracted two random

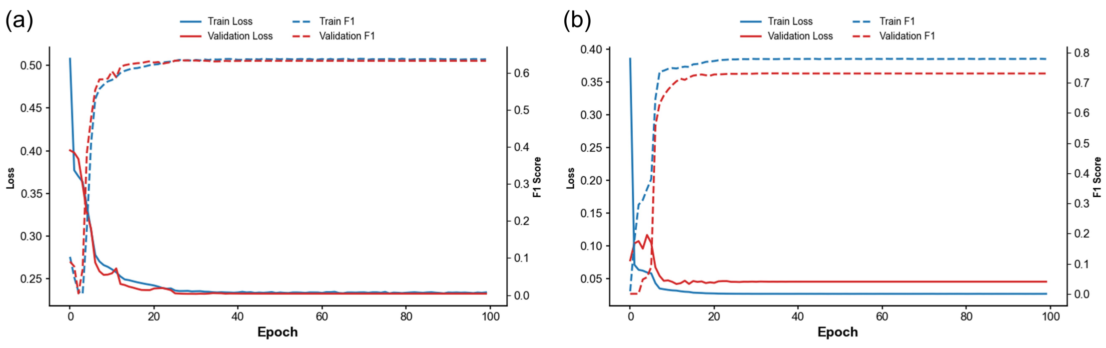

Fig. 6 AI model training performance evaluation of (a) early-stage wildfire model and (b) large-scale wildfire model.

time points from Videos S1 and S2, as illustrated in Figs. 7 and 8. The first example (Fig. 7) demonstrates wildfire progression from 2 to 10 h under a 12 mph west wind. The second example (Fig. 8) corresponds to Ignition 1 under a 6 mph south wind after 38 hof simulation. Visual comparisons in Figs. 8(a) and 8(b) reveal a strong alignment between the AI predictions and the benchmark, reinforcing the model's capability in forecasting wildfire burnt areas.

To quantify prediction accuracy, we applied a binarization threshold of 0.3 to the model's probabilistic outputs, classifying values above this threshold as burnt (1) and those below as unburnt (0). The differential maps (Figs. 7(d) and 8(d)) highlight prediction discrepancies, with white regions indicating areas of divergence. Overall, the large-scale wildfire predictions exhibit high accuracy (~85%), with errors remaining below 15%. However, the model's performance degrades in early-stage predictions, where errors rise to approximately 40%. This suggests that while the model excels in mid-to-late-stage fire spread estimation, further refinement is needed to improve early-phase forecasting.

3.3 Software case demonstration

The Intelligent Wildfire Forecast Tool (IWFTool) is a specialized software platform developed as part of this study, integrating the aforementioned workflow and advanced AI algorithms. This tool is designed to provide accurate and reliable predictions of wildfire spread over a 72-h period for Hong Kong Island. By leveraging deep learning techniques, the IWFTool aims to bridge the gap between theoretical research and practical firefighting applications, offering a user-friendly solution for operational wildfire modeling and forecasting.

The IWFTool is designed to facilitate AI-driven wildfire prediction by providing an accessible platform for researchers and firefighting professionals. Unlike traditional modeling approaches that demand specialized expertise and intensive computational resources, the IWFTool simplifies wildfire spread prediction through an intuitive interface (Fig. 9) and streamlined workflows. By minimizing technical barriers, the tool enhances real-time decision-making for wildfire preparedness and mitigation.

As showcased in Video S3, users can input critical environmental parameters (e.g., wind speed/direction, humidity, temperature, and ignition location) that directly influence fire behavior. The interface also integrates geospatial data layers, including satellite imagery, elevation maps, and slope gradients, to contextualize predictions for Hong Kong Island's

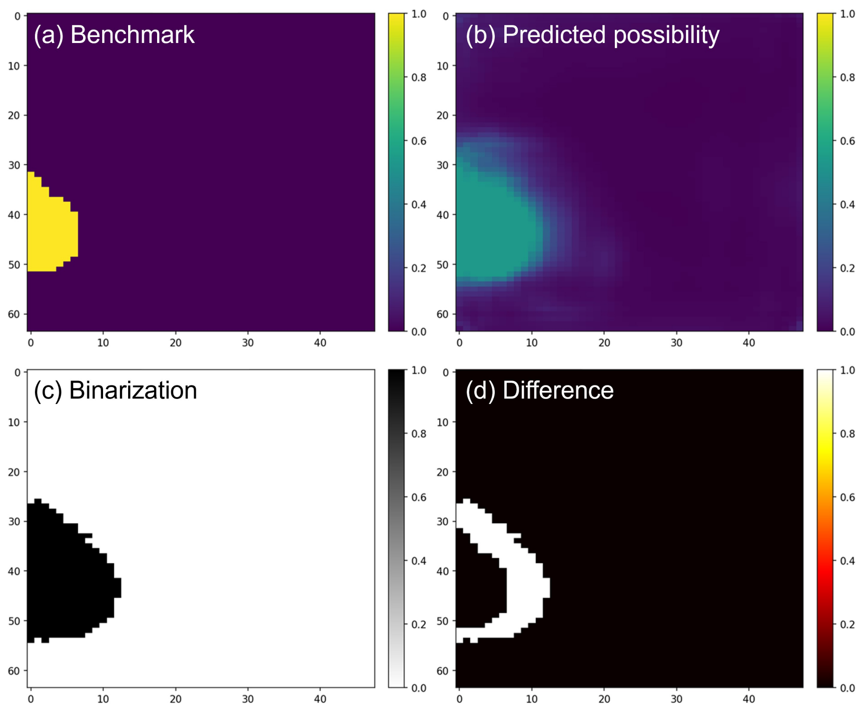

Fig. 7 Early-stage wildfire mode comparison between simulation results and AI predicted performance, (a) the benchmark of case with ignition 4, twelve mph of wind speed and West wind direction in 4 h, (b) AI predicted possibility of wildfire spread, (c) binarization of predicted possibility and (d) differences between simulation results and AI predicted performance.

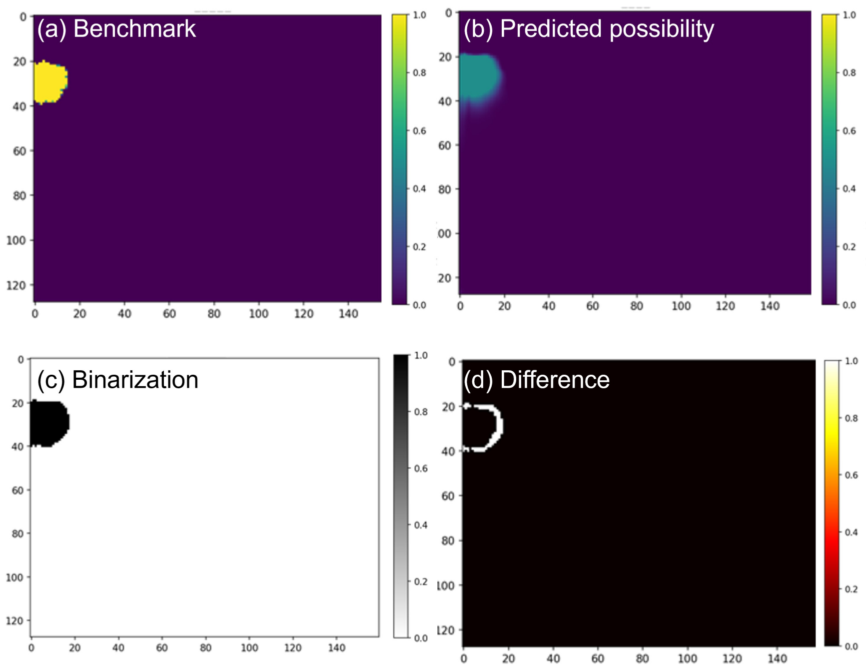

Fig. 8 Large-scale wildfire model comparison between simulation results and AI predicted performance, (a) the benchmark of case with Ignition 1, six mph of wind speed and South wind direction in 38 h, (b) AI predicted possibility of wildfire spread, (c) binarization of predicted possibility and (d) differences between simulation results and AI predicted performance.

unique terrain. Upon parameter submission, the tool rapidly generates wildfire spread forecasts, enabling users to visualize fire progression at customizable time intervals within seconds. This computational efficiency supports dynamic scenario analysis for emergency response planning.

The IWFTool bridges advanced AI modeling with practical firefighting needs through three key innovations:

1. **User-centric design**: Intuitive controls reduce reliance on technical expertise.

2. **Comprehensive data integration**: Combined parameter and geospatial inputs improve simulation accuracy.

3. **Real-time processing**: Near-instant forecasts facilitate timely interventions.

By translating cutting-edge research into operational tools, the IWFTool advances wildfire management in complex wildland-urban interfaces ultimately mitigating risks to public safety and infrastructure.

3.4 Perspectives and future work

While the current implementation of the model assumes constant wind speed and direction throughout the simulation period, it is important to acknowledge that such conditions are rarely observed in real-world scenarios. Wind dynamics are inherently variable, often exhibiting significant fluctuations in both speed and direction over short timeframes. These variations can profoundly influence wildfire behavior, including the rate and direction of fire spread. The assumption of constant wind conditions, though simplifying the computational process, represents a limitation of the current model. Addressing this limitation is a priority for future work, where we aim to incorporate time-varying wind fields to better reflect real-world conditions and enhance the accuracy of wildfire spread predictions.

In addition to improving the representation of wind dynamics, we plan to integrate large language models (LLMs) into the software to facilitate more intuitive and interactive user experiences, as shown in Fig. 10. LLMs, with their advanced natural language processing capabilities, can serve as intelligent assistants, enabling users to interact with the software using natural language queries. For instance, users could request specific wildfire simulations, ask for explanations of model outputs, or seek guidance on parameter selection. This integration aims to lower the technical barriers for non-expert users, making the tool more accessible to a broader audience, including firefighting personnel, emergency responders, and policymakers.

By addressing these limitations and incorporating advanced features such as LLMs, we aim to enhance the robustness, usability, and practical applicability of

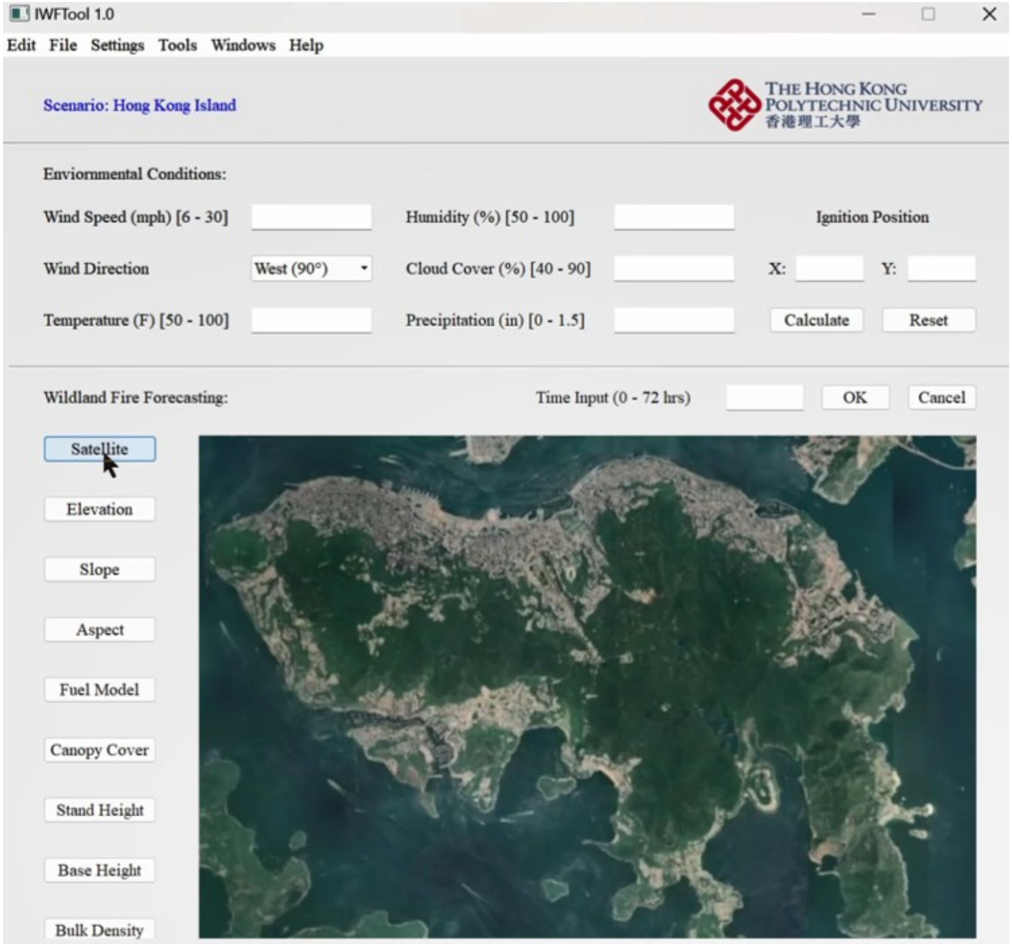

Fig. 9 User interface of the Intelligent Wildland Fire Tool.

the software. These improvements will not only advance the state-of-the-art in wildfire modeling but also contribute to more effective wildfire management and mitigation strategies, ultimately reducing the risks posed by wildfires in the world.

4 Conclusions

Wildfires, as cross-scale natural hazards, present a complex and dynamic challenge that requires innovative and adaptive solutions to mitigate their devastating impacts. The proposed framework, which incorporates cross-scale segmentation, addresses the complexities of wildfire spread by distinguishing between early-stage ignition dynamics and large-scale fire propagation behaviors. This approach not only simplifies the modeling process but also enhances computational efficiency, enabling rapid, high-resolution fire spread forecasts that are critical for real-time decision-making. Furthermore, the integration of this methodology into the user-friendly wildfire software AIWF-Tool offers a scalable and accessible solution for firefighting agencies and emergency responders, bridging the gap between advanced research and practical applications.

Despite these advancements, several limitations remain, such as the assumption of constant wind speed and direction in the current model, which does not fully reflect real-world variability. Future work will focus on incorporating time-varying wind fields and other dynamic environmental factors to improve the accuracy and realism of wildfire simulations. Additionally, the integration of large language models into the software is planned to enhance user interaction and accessibility, making the tool more intuitive for non-expert users.

In conclusion, this study contributes to the growing body of research on AI-driven wildfire modeling by proposing a multi-stage framework that addresses the complexities of cross-scale wildfire behavior. By

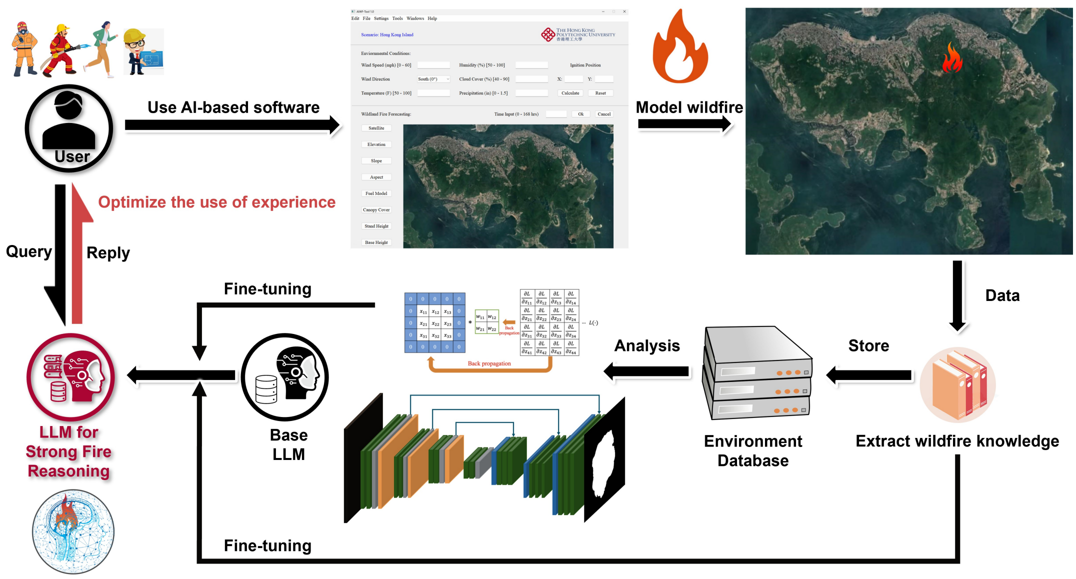

Fig. 10 Combination of large language models with wildfire software to optimize the use of experience.

combining advanced computational techniques with practical applications, this work aims to support more effective wildfire management and mitigation strategies, ultimately reducing the risks posed by wildfires to human life, property, and the environment.

CRediT Authorship Contribution Statement

Yizhou Li: Formal analysis, Investigation, Methodology, Writing-original draft; **Yanfu Zeng:** Formal analysis, Investigation, Software; **Zhiqing Pan:** Resources; **Xinyan Huang:** Conceptualization, Funding acquisition, Methodology, Supervision, Writing-review & editing.

Conflicts of Interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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