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Super Real-Time Forecast of Wildland Fire Spread by A Dual-Model Deep Learning Method

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ABSTRACT. Driven by climate change, more frequent and extreme wildfires have brought a greater threat to humans globally. Fast-spreading wildfires endanger the safety of residents in the wildland-urban interface. To mitigate the hazards of wildfires and facilitate early evacuation, a rapid and accurate forecast of wildfire spread is critical in emergency response. This study proposes a novel dual-model deep learning approach to achieve a super real-time forecast of 2-dimensional wildfire spread in different scenarios. The first model utilizes the U-Net technique to predict the burnt area up to 5 hours in advance. The second model incorporates ConvLSTM layers to refine the forecasted results based on real-time updated input data. To evaluate the effectiveness of this methodology, we applied it to Sunshine Island, Hong Kong, and generated a numerical database consisting of 210 cases (12,600 samples) to train the deep learning models. The simulated wildfire spread database has a fine resolution of 5 m and a time step of 5 minutes. Results show that both models achieve an overall agreement of over 90% between numerical simulation and AI forecast. The real-time wildfire forecasts by AI only take a few seconds, which is $10^2 \sim 10^4$ times faster than direct simulations. Our findings demonstrate the potential of AI in offering fast and high-resolution forecasts of wildfire spread, and the novel contribution is to leverage two models which can work in tandem and be utilized at various stages of wildfire management.

Keywords: wildfire prediction, artificial intelligence, fire modelling, wildland-urban interface, prescribed burning, smart firefighting

1. Introduction

Fire has been a long-existent phenomenon on Earth and an essential part of different ecosystems (Running, 2006; Belcher, 2013). With the rise of human civilization and the expansion of living space, humans are gradually occupying the wildlands to create more urban areas. Meanwhile, our human activities have caused more and more wildfires and increased the frequency of extreme wildfires. Once a wildfire occurs (Figure 1a), it primarily affects the residents who live in the emerging wildlandurban interface (WUI) (Theobald and Romme, 2007; Gill and Stephens, 2009). Driven by climate change and the extreme dry season, even if the initial ignition points are minor and far away from the urban areas, wildfires could threaten the safety of residents after rapidly spreading for hundreds of kilometers across states and countries. Wildfire has become a global natural disaster that concerns many countries and regions (Jolly et al., 2015; Walker et al., 2020; Witze, 2020).

Wildfire behavior is a complex and dynamic phenomenon influenced by various factors, including the characteristics of the fuel, topography, weather conditions, and local landscape. As such, fire spread is not always linear or steady-state, and predicting its course can be challenging. In particular, sudden changes in weather conditions or the ignition of new fires can cause rapid shifts in the pattern of wildfire spread, potentially breaching established firebreaks and endangering previously safe areas. Therefore, accurate forecasting of real-time or shortterm trends in fire spread is essential for effective wildfire management, particularly in wildland-urban interface (WUI) zones. Real-time fire spread forecasts can aid fire services in allocating resources, planning evacuations, and implementing other emergency response measures by predicting a fire's expected trajectory and intensity. These predictions can also assist residents in making informed decisions about their safety and help to prevent loss of life and property damage.

On the other hand, to reduce the hazards of extreme wildfires in the dry season, prescribed or culture burning has been an effective strategy for reducing fuel loads (Fernandes and Botelho, 2003; Penman et al., 2011). Forest services and firefighters often adopt this proactive defensive method to reduce fuel accumulation in the wildland. Nevertheless, prescribed burning often gets out of control and becomes a new wildfire, like the 2022 Calf Canyon/Hermits Peak Fire in New Mexico, USA (Nevins, 2022). Thus, it requires precautions and new technology to plan and monitor the prescribed burning development. In short, a real-time forecast of the 2-D burnt perimeter for a spreading wildland fire provides a critical reference in both the long-term fire management and the emergent decision-

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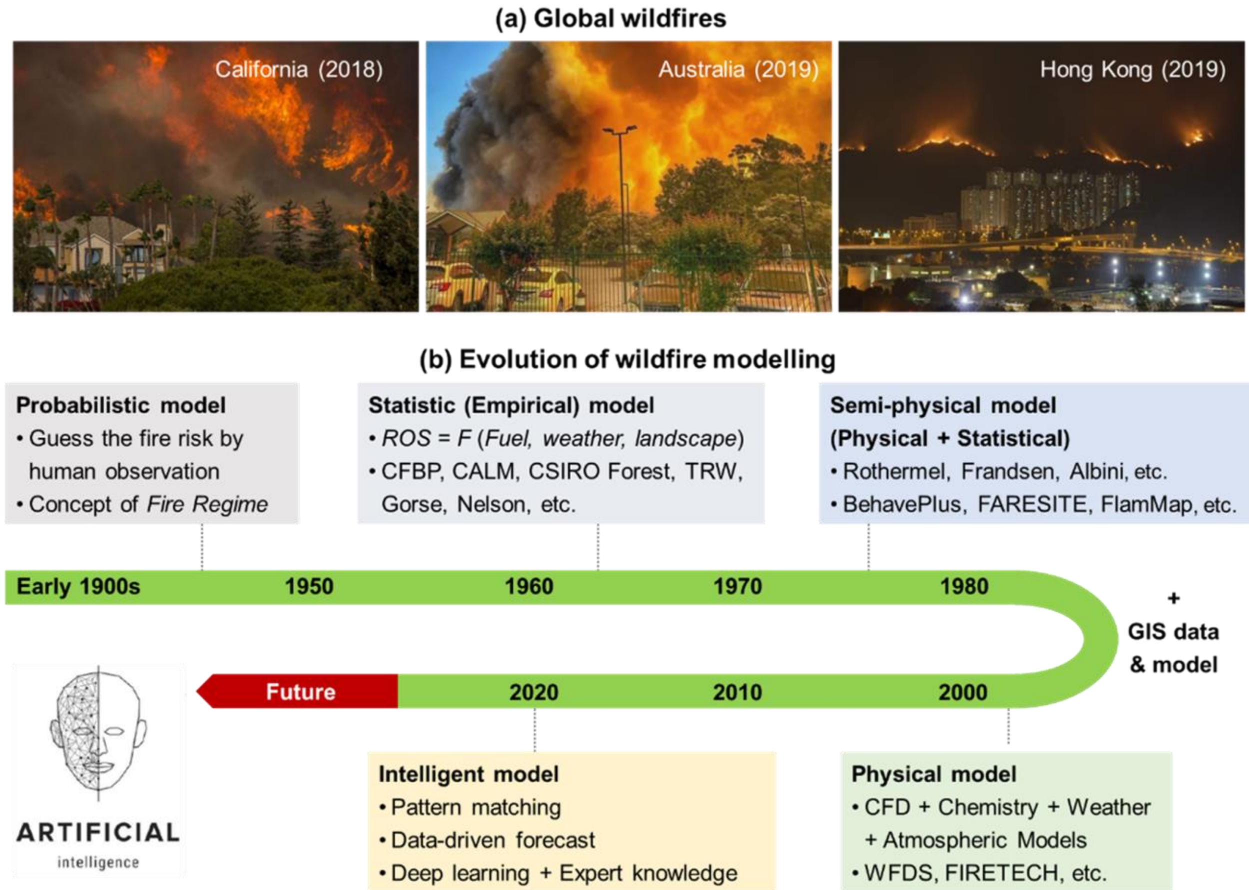

Figure 1. (a) Recent global wildfire incidents and (b) the historical evolution of wildfire modelling.

making of firefighting, evacuation, and rescue.

Researchers have attempted to simulate wildfires and forecast their spread behaviors since the 1950s or even earlier (Figure 1b). In the early days, most models were simple and probabilistic, based on limited human observation and experience. These models mainly assessed the wildfire risk but could not predict wildfire spread (Skinner and Chang, 1996). Later in the 1970s, more understanding of wildfire dynamics was introduced to the mathematical model. Notably, Rothermel proposed a widely used semi-physical formula that considers different factors of fire, fuel, landscape, and weather to calculate the wildfire spread (Rothermel, 1972). In the 1990s, several software tools had been developed to program these semi-physical models and environment parameters to predict 2-D wildland fire spread. For example, FARSITE (later becoming a part of FlamMap) coded Rothermel's equation to simulate and visualize wildfire propagation (Finney, 1998). The running of FARSITE needs input from the Geography Information System (GIS), but the data from wildland fuel, weather, and landscape are often challenging to acquire accurately.

Since the 2000s, several numerical software was developed for physics-based fire modellings, such as HI- GRAD/FIRETEC and Wildland Fire Dynamics Simulator (WFDS) (Hoffman et al., 2016). These tools are based on computational fluid dynamics (CFD) that can solve the atmospheric flow field and ground boundary flow near the fire (Anderson and Wendt, 1995). These tools make wildfire simulation exquisite but consume considerable time and require high computation costs. Overall, the wildfire modelling method is evolving from statistics-based models to physical-based models. Nevertheless, all these computational tools are too slow to give real-time forecasts of wildland fire development. For example, forecasting the wildfire front in a few minutes often takes CFD-based software to run hours, so these kinds of wildfire simulations neither help guide the wildfire emergency response nor plan the prescribed burning.

1.1. Research Motivation

While semi-physical modelling provides a faster alternative to computational fluid dynamics (CFD) modelling, it still requires several or more minutes for a single case. For example, in the case of firefighters needing to evaluate hundreds of scenarios for prescribed burning, semi-physical modelling would require one or two days to demonstrate all cases. This make real-time modelling a more viable option for generating comprehensive plans in a limited time frame. Moreover, semi-physical modelling is unsuitable for on-site wildfire situations requiring real-time forecast output for decision-making.

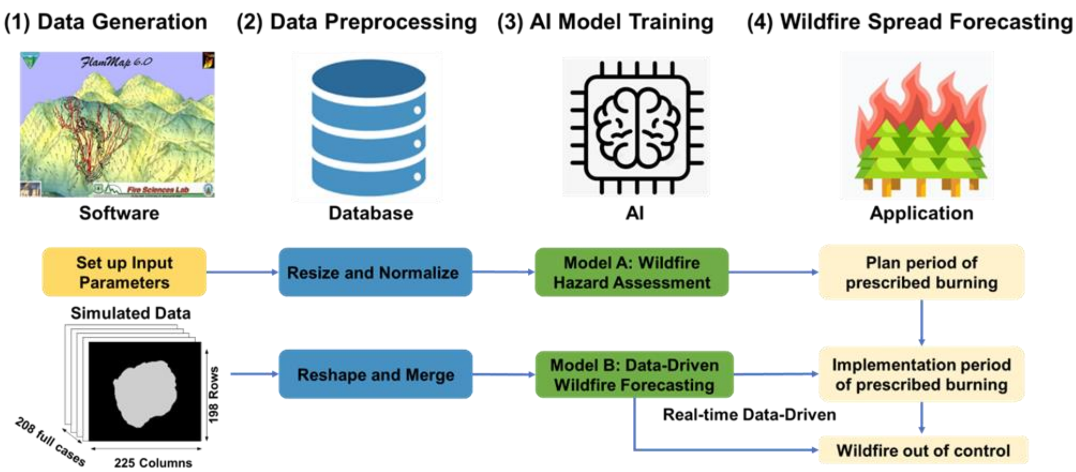

Figure 2. Process of the whole methodology with four major steps to realize the wildfire spread forecast.

To overcome the above issues, more recently, new artificial intelligence (AI) models have been proposed for fire forecast (Wang et al., 2022; Wu et al., 2022; Zhang et al., 2022), including wildfire forecast, which is an emerging research topic (Radke et al., 2019; Allaire et al., 2022; Jiang et al., 2022). The mathematic-based computation can be switched into a data-driven matchup in the database, where AI models calculate the mathematical relations among different parameters within seconds. Many researchers optimized the traditional models with AI models to increase the accuracy of forecasts (Radke et al., 2019; Zhou et al., 2020). Also, deep learning was widely used to explain and predict the wildfire spread rate (Zhai et al., 2020; Storey et al., 2021; Li, Lin, et al., 2022). Deep learning models were also adopted to map and forecast the wildfire risk possibility (Jaafari et al., 2019; Le et al., 2020; Allaire et al., 2022). Meanwhile, the AI-based models primarily decreased the computation time and made the long-term forecast possible in simulating wildfires (Hodges and Lattimer, 2019; Sung et al., 2021; Li, Zhang, et al., 2022). By leveraging the power of AI, this approach allows for more accurate and efficient prediction of fire behavior and can provide critical information to support decision-making in firefighting operations.

However, these past studies focused on simulating or forecasting the wildfire spread with low-resolution satellite data and giant time steps. Specifically, the input simulated cell size is the same size as the GIS pixel (usually 30 × 30, 200 × 200, 2 k × 2 k m^2 or larger) (Hodges and Lattimer, 2019; Jaafari et al., 2019; Allaire et al., 2021; Li et al., 2022). These models heavily rely on GIS data that are either in low resolution or not in real- time. Thus, they cannot handle high-resolution and real-time wildfire images from unmanned aerial vehicles (UAVs), the state-of-the-art remote sensing data acquisition in ecosystem management (Burgués and Marco, 2020). Moreover, previous findings can neither monitor early-stage wildfires with a burning area smaller than the pixel size of satellite images nor calibrate the forecasted burnt area by real-time UAV images in a real wildfire scene.

This study proposes a dual-model deep learning method to forecast the wildfire spread in different fire scenarios. The simulated wildfires are recorded in a short time step of 5 min and a fine cell size of 5 × 5 m^2 that fits the input of UAV imaging. A numerical database with hundreds of wildland fire scenarios in an island of Hong Kong is established for demonstration. Two deep learning models (U-Net and ConvLSTM) are trained by the database for pre-fire risk assessment and real-time emergence response in a wildfire. Compared to traditional simulation-based methods used mainly in wildfire post-accident analysis, our method demonstrates $10^2 \sim 10^4$ times faster in wildfire modelling and achieves real-time forecast. The accuracy and reliability of models are tested by random wildfire scenarios, which lay a foundation for future intelligent wildfire fighting and management.

1.2. Contributions

This work has made several significant contributions to the field of wildfire modelling and management. The main contributions of this work are summarized as follows:

- A review of the development of wildfire modelling was conducted, emphasizing the need for AI-based wildfire modelling approaches that can provide accurate predictions of fire behavior.
- One specific issue identified and addressed in this study is the challenge of forecasting wildland fire spread relying on low-resolution satellite data and large time steps. A numerical wildfire database was established with 5-m high-resolution images specifically for Hong Kong to overcome this challenge. This database establishment method provides a valuable resource for improving wildfire modeling and forecasting accuracy and resolution.
- A novel dual-model deep learning method was first proposed to achieve super real-time forecasts in wildfire management. By leveraging the information in the numerical wildfire database, the two models can work in tandem and be utilized at various stages of wildfire management, addressing the shortcomings of single-AI model methods without self-calibration.

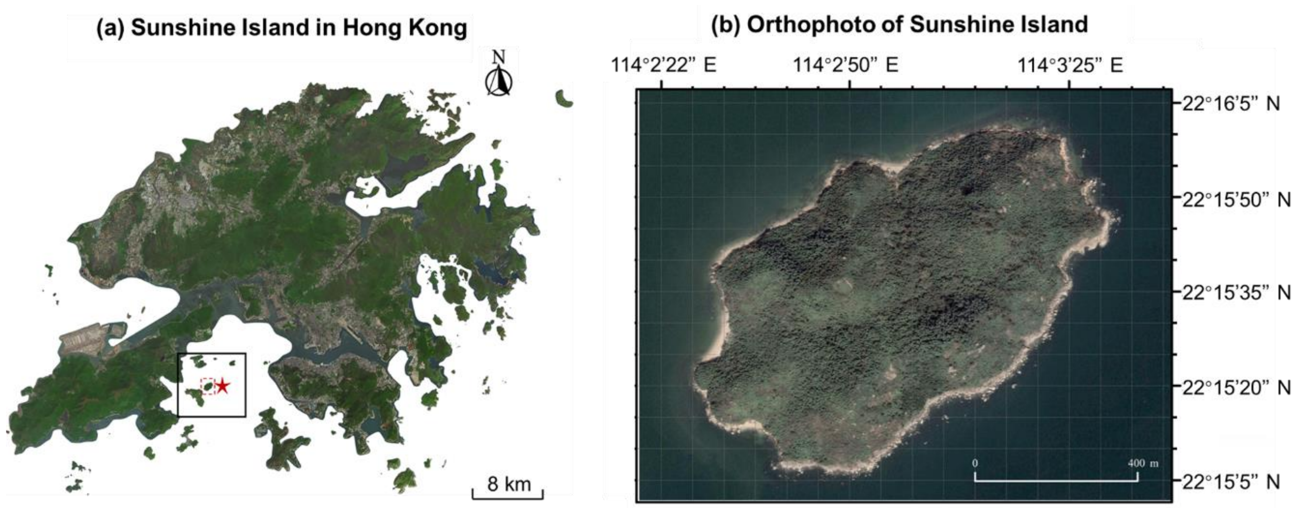

Figure 3. The Sunshine Island in Hong Kong, (a) its location with a red star (proposed artificial islands inside the black line), and (b) the orthophoto of Sunshine Island (from Google Earth Pro).

- This work provided a new deep learning-based framework for a fast and smart emergency response to earlystage wildland fires. By enhancing our ability to predict and manage wildfires, this research can help to improve global wildfire safety and reduce the risk of property damage and loss of life.

2. Methodology

The target of our study is to forecast any wildfire spread situation with a lead time of 5 hours and in a short time step of 5 min. With this tool, we can assess the fire hazard before implementing the prescribed burning or forecast wildfire burnt areas more accurately by feeding high-resolution UAV images. While actual data on wildfire spread is the most suitable for training the model, it is often limited due to infrequent occurrences of fires on the same land and a lack of adequate footage to reconstruct the whole process. Hence, this study used numerical wildfire scenarios to create the database. These scenarios enabled the development of accurate and efficient models for wildfire forecasting, providing valuable tools for enhancing wildfire management strategies.

Compared to the numerical database in the literature (Arca et al., 2007; Zigner et al., 2020), our database includes not only massive simulated wildfire scenarios but also very fine resolution and short time steps to support emergency response. Herein, wildfire spread processes are generated by FlamMap 6, which runs the code of FARSITE (Finney, 1998, 2006). Figure 2 shows the whole flow chart of the proposed methodology. It includes four steps, (1) using FARSITE to simulate hundreds of wildfire spread cases beforehand, (2) building a database of numerical wildfire simulations after preprocessing, (3) training the dual-model deep learning method with the database, and (4) applying random fire cases and deep learning models to achieve super real-time forecast of the wildfire.

Hong Kong is a highly populated modern city with over 4,000 skyscrapers, but it also has ~70% of its land covered by woodland, shrubland, and wetland (Lee et al., 2017). Therefore, it is a typical WUI that is constantly threatened by wildfires. According to the data from Hong Kong Fire Services Department ('Hong Kong Fire Services Department - Access to Information', 2021), about 1,000 wildfires (or hill fires) are reported annually. Over 80% of wildfires witness a burning area of less than 1,000 m^2 and a burning time of 24 h because of significant firefighting efforts. Still, some wildfires spread to nearby high-population urban areas that cause significant safety issues and air pollution.

To prove the applications of wildfire forecast in Hong Kong, Sunshine Island, also called Chau Kung To indigenously, is chosen as the study area (Figure 3). It has an area of 0.54 km^2, a total border length of 3.1 km, with a homogeneous vegetation type. The island is so tiny that it will be shown in fewer than 10 pixels in a typical image from MODIS satellites. Thus, GIS data is almost impossible to monitor any wildfire on this island. Instead, it is perfect for one or more UAVs to monitor wildfire development and firefighting processes on this small island. Moreover, the limited area and homogeneous vegetation type make this island an ideal demonstration to train and verify the AI model. This island is also a crucial part of Hong Kong's Lantau Tomorrow Vision (Wang et al., 2019; Fung, 2020), which is a future plan to reclaim land from the sea and develop new residential areas.

Thus, understanding the wildfire hazard of this area is critical for the safe future development of Hong Kong, and the methodology can also provide the basis for small-scale global wildfires. Interested parties can develop their own database, replicate the training process, and apply the same methodology to their region of interest.

2.1. Physics-Based Modelling and Input Parameters

Despite multiple wildfires that occurred on Sunshine Island historically, there is limited information on these past fire cases. Thus, modelling the wildfire spread numerically is the

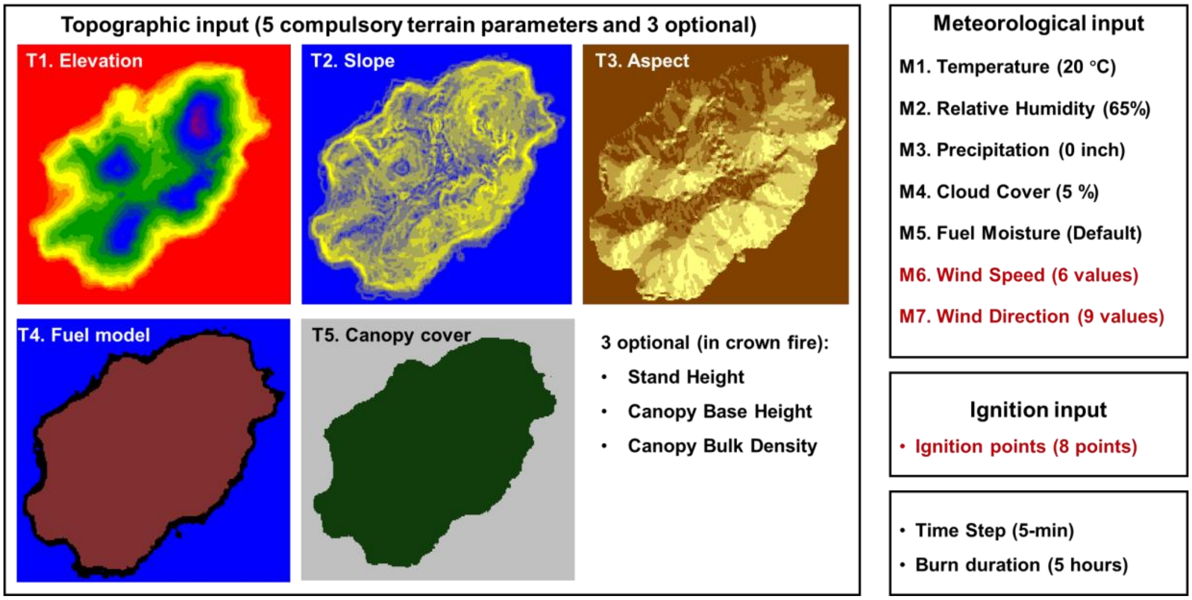

Figure 4. Required input parameters of FARSITE in the modelling.

only way to create a database. FARSITE (Finney 1998) is developed and widely used by the U.S. Forest Service as an effective tool for simulating the wildfire spread process and evaluating the burning areas (Srivas et al., 2016). The software solves the wildfire-spread equation proposed by Rothermel and Albini (Rothermel, 1972; Albini, 1985), so it can predict the 2-D perimeter of the burnt area, defined by the fastest local rate of fire spread and its direction. Therefore, this work uses numerical wildfire cases generated by FARSITE. It is worth noting that the numerical results have similar patterns as the real scenario wildfire data, as FARSITE is often used for planning prescribed burning and reconstructing the wildfire history for post-fire analysis (Wu et al., 2013; Benali et al., 2016, 2017).

FARSITE is a semi-physical tool that assumes a constant wildfire spread rate within each cell, regardless of its size (5 × 5 m^2 or 2 × 2 km^2). This approach becomes unrealistic when the cell size is very large, but the fire is relatively small. Although FARSITE's calculation speed (in the order of minutes and hours) is much faster than CFD-based simulation (in the order of days), it still cannot forecast fast-changing wildfires or support immediate decision-making by fire and forest services. Furthermore, during the simulation, FARSITE cannot incorporate real-time input parameters, such as changing wind speed and direction. Therefore, a more flexible and faster AI-based wildfire forecasting method is needed to support real-time emergency response in complex fire behaviors and environmental changes. The models developed in this study provide a viable solution to these challenges and enable accurate wildfire forecasting, incorporating real-time input data from various sources, such as UAVs, to support effective decision-making by firefighting agencies.

Running any wildfire simulation requires a significant number of inputs related to topography, meteorological conditions, and burning parameters. For example, in the case of crown fires, the software requires five critical terrain parameters and three optional topography parameters, according to Finney (1998). These parameters define the landscape and fuel type, which do not change with time, weather, or ignition. Additionally, seven meteorological input parameters and one ignition parameter are needed to simulate the effect of weather, season, and ignition. The values of these parameters can be changed directly in the software before running the simulation.

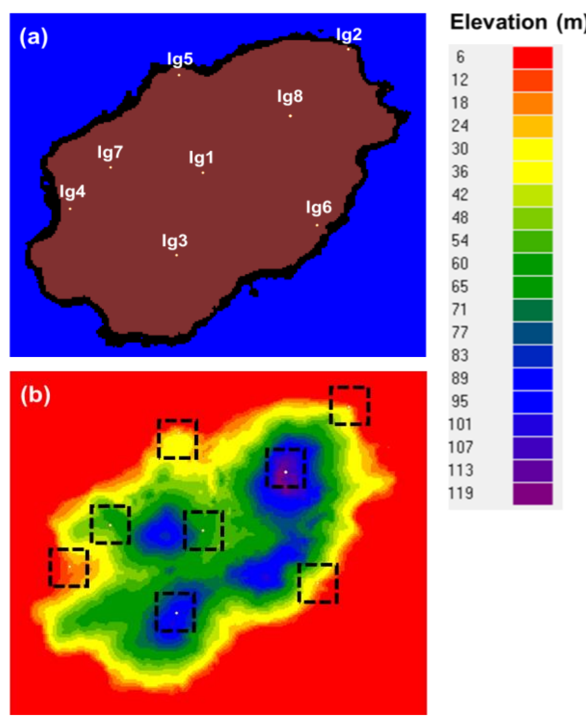

Figure 5. (a) Labels of 8 ignition points and (b) locations in elevation maps.

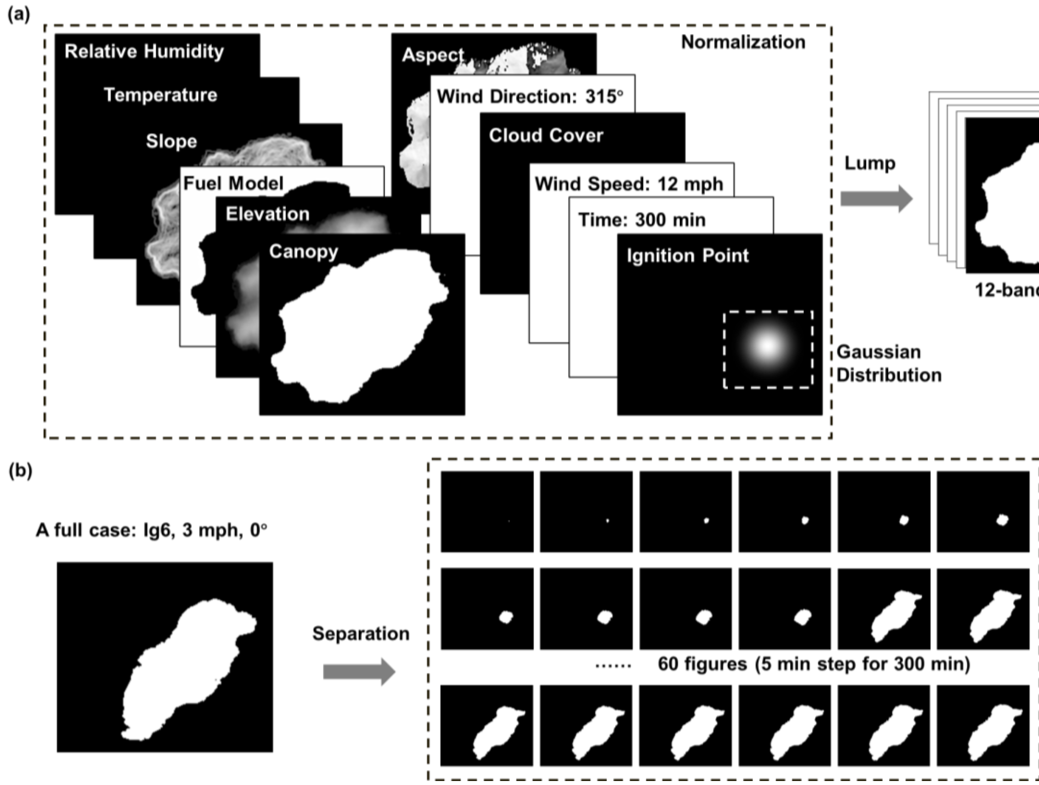

Figure 6. Preprocessing demonstration, (a) input preprocessing: a case of normalization and the lump in 12 parameters, and (b) output preprocessing: a case of extract time from the full case.

For instance, Figure 4 lists the input parameters required for simulating wildfires on Sunshine Island. These inputs provide a foundation for accurately modeling and forecasting wildfire behavior, supporting effective decision-making by firefighting agencies.

The land elevation data for this island was directly obtained from the Hong Kong government's open-source website. Subsequently, ArcGIS 10.2 software was used to post-process this data, resulting in a 5-meter resolution image obtained through remote sensing techniques. The slope and aspect data were also derived from the elevation information using ArcGIS 10.2 with the exact pixel resolution. We considered local vegetation types to customize the fuel model and canopy cover, and an expanded standard NFFL fuel model (Scott and Burgan, 2005) was employed. In order to set meteorological inputs, average values during high fire-prone seasons were utilized.

Once all parameters for a given case have been input, FARSITE can run the wildfire simulation and generate burnt area data at each time step. Depending on the simulation time, time step, input resolution, and computational abilities, a single case can take anywhere from several minutes to several hours to complete. In order to create a large database of wildfire scenarios for AI training, we varied three key parameters (ignition location, wind speed, and wind direction) while keeping all other parameters constant. In the training dataset, each ignition point is associated with four different wind speed values and eight wind directions. Additional random parameters were selected for the testing dataset to test our AI models' feasibility and generalization ability. In total, 210 wildfire cases are simulated, as listed in Table 1.

Figure 5 depicts the eight ignition locations randomly selected to cover the island's internal and border areas. These locations were chosen to reflect the geographic features of the entire island and include varying elevations (as shown in Figure 5b). Each case has one fixed ignition point, one fixed value of wind speed, and one fixed value of direction.

To train and test our deep learning models, we divided the total number of wildfire cases into two separate datasets: 192 for training and validation and 18 for blind testing. The sum of these two datasets results in a total of 210 full cases (as indicated in Table 1). Each case comprises 60 images of the burnt area obtained after preprocessing (as described in Section 2.2), with one image generated every 5 minutes during the entire 300-minute (or 5-hour) duration of the simulated wildfire spread. These simulation results represent the burnt area where wildfires have spread over the course of 5 hours following ignition. The image resolution is 198 × 225 pixels, with each pixel covering an area of 5 × 5 square meters. This fine resolution allows for visualization of the wildfire spread at a time step of 5 minutes. Due to the finer pixel size compared to previous research, these data could not only be derived from GIS data but also obtained from on-site UAV images.

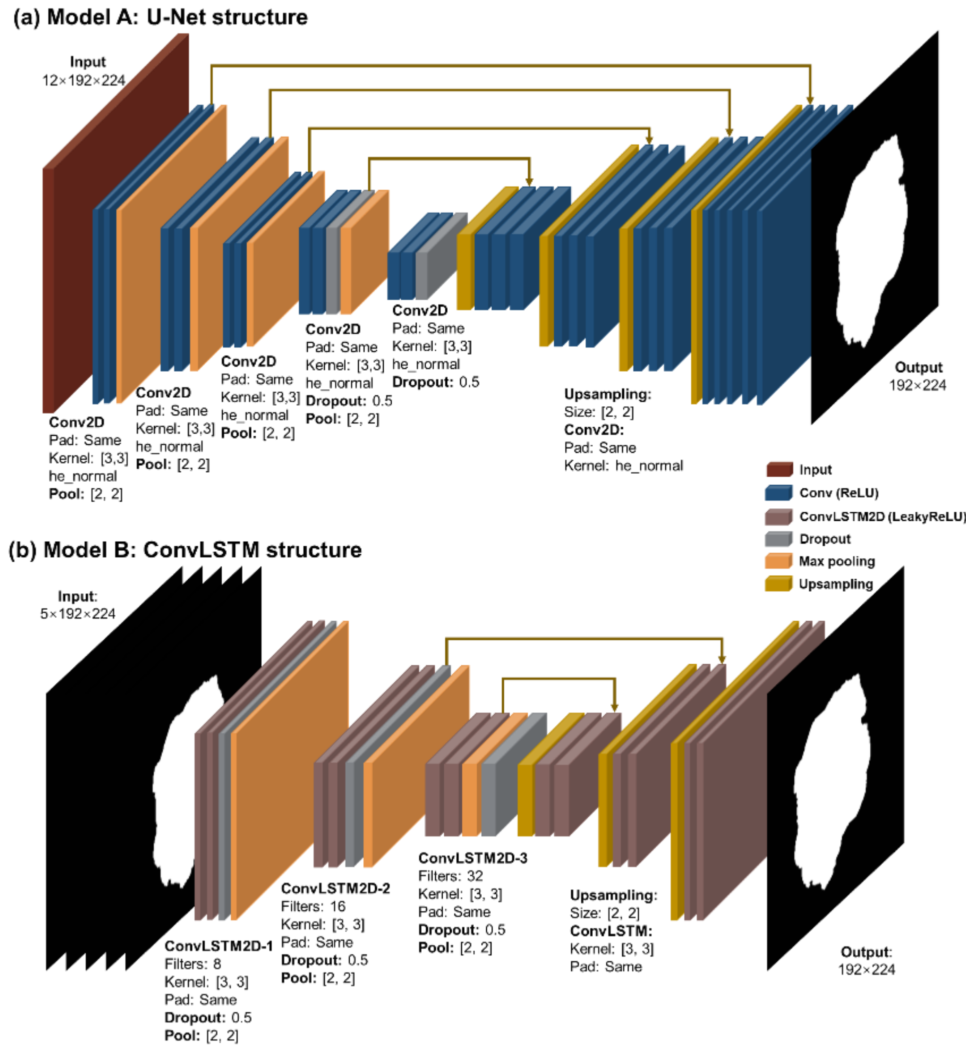

Figure 7. AI model structure in the paper, (a) U-Net structure and (b) ConvLSTM structure.

2.2. Data Pre-Processing to Form the Database

Two distinct steps are taken to preprocess input parameters and output simulation results. Firstly, input parameters are normalized to facilitate training (as shown in Figure 6a). This involves normalizing the values of all parameters within each pixel to range from 0 to 1. Additionally, Model A selects 12 parameters (T1-5, M1, M2, M4, M6, M7, ignition location, and time) as the primary input data for later training. These parameters are then combined into a single 12-band image for each time step of each case. Since M3 and M5 are default parameters during simulation, they are not included in the AI model input.

During the entire simulation process, three meteorological inputs (temperature, humidity, and cloud cover) remain unchanged. Therefore, these bands are pre-filled with a value of 0 in each pixel. In future work, we plan to consider the more complex meteorological influences by examining the effect of season and climate on wildfires. Additionally, the ignition point is specially handled using Gaussian distribution around the initial pixel, as suggested by (Tompson et al., 2014). This preprocessing step is crucial to ensure that the kernel (3 × 3) can effectively extract the feature map of ignition points during model training. Wildfire images depicting burning and spread over a duration of 5 hours are generated from all 210 cases, where the white pixel (with a value of 1) represents the burnt area. However, the lack of any discernible pattern over time poses a challenge for subsequent image processing. A separation algorithm has been proposed to extract the time data from the simulation results to address this issue. Through this algorithm, all wildfire evolution images in each case can be divided into 60 images, each representing a time step of 5 minutes between 5 and 300 minutes (as shown in Figure 6b).

Following preprocessing, a large database is established for AI model training, pairing input, and output data at every time step. The entire database comprises 12,600 (210 cases × 60 images) 12-band input images as well as 12,600 wildfire evolution images. To facilitate deep learning training, all data (or images) are resized to 192 × 224 pixels, as the neural network requires image resolution to be a multiple of eight to go through

4 times pooling. AI models will be trained using this database to achieve the desired forecasting objectives.

2.3. A Dual-Model Deep Learning Method

This section introduces the basic methodology and structure of two proposed deep-learning models (Figure 7). These two models both share the same database but require different inputs in adaptation to different wildfire scenarios.

The selection of deep learning models for a given task is contingent upon the characteristics and requirements of that task. For the purpose of prescribed burning planning, we choose the semantic segmentation algorithm to realize the wildfire forecast, employing a binary representation scheme in which unburnt areas are denoted by 0 and burnt areas are represented by 1. The U-Net algorithm, known for its efficacy in segmentation tasks, has been selected to achieve this objective. During actual wildfire scenarios, temporal and spatial data play a crucial role in predicting the spread of wildfires. Therefore, ConvLSTM, which combines the convolutional neural network (CNN) with long short-term memory (LSTM), is employed to forecast the propagation of wildfires. Incorporating LSTM algorithms within the ConvLSTM model enables it to capture long-range dependencies of sequential data. This makes ConvLSTM particularly suitable for modelling dynamic systems such as wildfire spread, where the evolution over time is highly correlated with the spatial location.

2.3.1. Model A: Wildfire Hazard Assessment

Model A is a U-Net model, one of the earliest algorithms for semantic segmentation using fully convolutional networks. The U-Net architecture utilizes a symmetric U-shaped structure consisting of compressed and extended paths (Ronneberger et al., 2015), from which it derived its name. The entire model structure of the U-Net used in this paper is depicted in Figure 7a. This network is a classic fully convolutional network and does not require any fully connected operations. Convolutional layers are used to extract local features from small sub-regions within the images that contain geographic information. Subsequently, information on these features can be fused into the subsequent processing stage to detect more advanced features, such as the probability of fire reflecting spreading trends.

The compress path of Model A comprises five blocks, with the first four blocks utilizing two convolutional layers and one max pooling layer for down-sampling. The last two blocks have two dropout layers to prevent overfitting during model training. During the up-sampling process, each block adopts one up-sampling layer and three convolutional layers, which are then concatenated with the down-sampling convolutions.

Model A takes 12-band images (as shown in Figure 6a) as input, containing a dozen adjustable topographic and meteorological parameters that can influence wildfire spread behaviors. The output of this model comprises corresponding wildfire evolution figures with a size of 192 × 224 pixels. In the training dataset, this model utilizes 11,520 samples of 12-band images (Input) and 11,520 wildfire evolution figures (Output) from the database.

2.3.2. Model B: Data-Driven Wildfire Forecasting

Model B is a ConvLSTM model that utilizes Long Short-Term Memory (LSTM) - a particular type of recurrent neural network (RNN) designed to address long-term dependency problems. LSTMs were introduced by Hochreiter and Schmidhuber in 1997 (Hochreiter and Schmidhuber, 1997) and are capable of processing temporal one-dimensional data. However, when the temporal data consist of images, traditional LSTMs cannot handle them as they require a multi-dimensional tensor input. Therefore, adding convolutional operations to LSTM is more effective for feature extraction of images (Shi et al., 2015). In this study, Model B (Data-driven Wildfire Forecasting) adopts the ConvLSTM structure to train the models (as shown in Figure 7b). Each block consists of 2 ConvLSTM layers, one max pooling layer, and one dropout layer to prevent overfitting during training. The three up-sampling blocks have two symmetry ConvLSTM layers similar to the down-sampling blocks.

The input format for Model B differs from that of the U-Net model. Here, five consecutive wildfire evolution figures with a time-step of 5 minutes (spanning a total duration of 25 minutes) are used to forecast the following wildfire evolution figure. Specifically, five figures with a size of 192 × 224 pixels serve as input, whereas one figure with the same size serves as output. This model uses 11,520 wildfire evolution figures from the database in training.

2.4. The Training Process of Two Deep Learning Models

To summarize, the database used for training both models comprises 11,520 preprocessed 12-band images. Normalization of inputs dramatically reduces the computation cost of model training.

The proposed U-Net framework contains convolutional, max-pooling, up-sampling, and dropout layers to avoid overfitting with a dropout value of 0.5. Binary cross-entropy and Adam serve as the loss function and optimizer. The dataset for training is divided into 32 batches, and the U-Net model is trained for 200 epochs with a train-validation data ratio of 9 : 1. In total, 174 cases are for training, 18 cases are for validation, and 18 blind cases are for testing. On the other hand, the ConvLSTM model does not require the normalization of input data types, and the input and output data types are identical., The dataset used for training has 10,560 samples and binary crossentropy, and Adam serves as the loss function and optimizer. These samples were divided into 20 batches, and the ConvLSTM model was trained for 100 epochs with a train-validation data ratio of 9 : 1. To determine the optimal values of these hyperparameters, random search and manual adjustment methods are performed on a subset of the dataset to evaluate the performance. Both models were trained on a server with 32 cores, 124 GB of physical memory, and a Tesla P100 GPU.

Model A (Wildfire Hazard Assessment) can support implementation plans and decisions regarding prescribed burning, which requires precautions for safety reasons. Model B (Data-driven Wildfire Forecasting) can forecast future fire spread locations based on real-time input from the current burning region in cases where wildfires are out of control. This model can aid

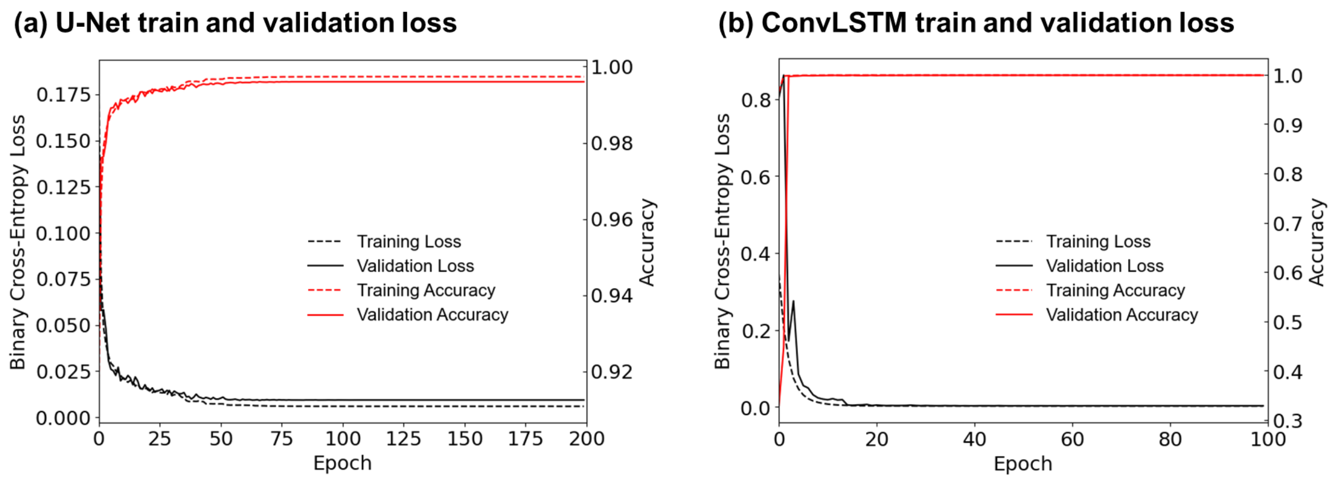

Figure 8. Loss values of two models: (a) loss and accuracy of U-Net structure, and (b) loss and accuracy of ConvLSTM structure.

decision-making in firefighting, evacuation, and rescue operations. Both models can work independently to address different wildfire issues and situations based on the needs of the forest and fire services department.

3. Results and Discussion

3.1. Model Performance Evaluation

The assessment of model performance is a critical aspect of deep learning applications. One popular method for evaluating the effectiveness of models involves the use of loss functions. Loss functions allow us to quantify the degree of difference between predicted outputs and actual values during the training phase. In this study, we employ binary cross-entropy as the loss function for both Model A (U-Net) and Model B (ConvLSTM). Binary cross-entropy is a commonly used loss function for image segmentation tasks and is particularly effective when binary values represent the output.

The loss function measures the distance between the predicted probability and the accurate distribution, with lower values indicating better model performance. By adopting binary cross-entropy as the loss function, we can evaluate the deviation between predicted 2-dimensional figures and simulated figures during the training phase. This approach allows us to train the models to accurately predict the burnt and unburnt areas in wildfire evolution images, enabling them to provide accurate forecasts for future fire spread locations. (Figure 8).

Figure 8 illustrates the evolution of loss values with more training epochs for both models. In the U-Net model, the loss value experiences a significant decline during the initial 50 epochs and minor variations while being trained. Eventually, both the training loss and validation loss stabilize at 0.0058 and 0.0093, respectively, indicating that the training has achieved the desired effect. Similarly, in the ConvLSTM model, the loss decreases significantly in the first 20 epochs. Subsequently, the training loss and validation loss become steady and nearly identical at 0.0023 and 0.0032, respectively. In both models, the accuracy value calculated by the model is over 99.0%.

Nevertheless, the loss value provides a clearer indicator of the rationality of our training. The predicted results take the form of a "heatmap" (Spitzer et al., 2014), where each pixel represents the likelihood of wildfire spread between 0 to 1 after the sigmoid activation function. These trained models will be further validated with several case demonstrations in the following section, using a pivotal metric to assess forecast results.

3.2. Forecasting of Wildfire Spread in Model A (Wildfire Hazard Assessment)

Table 1 summarizes the train data and test division for all cases. To demonstrate the feasibility of the trained models, a total of 18 full cases comprising 1,080 spread figures were used to evaluate model performance. Two selected cases (A1 and A2) are presented below and explained in more detail (refer to Videos S1 and S2 for a visual demonstration). In Case A1, the ignition point is set at point 1, the wind speed is 10 mph, and the wind direction is 0 degrees (south). Both the ignition point and wind direction variables exist in the training dataset. In contrast, Case A2 involves an entirely random selection of ignition point 7, a wind speed of 10 mph, and a wind direction of 200 degrees (north by east).

Case A1 (Ig1, wind speed = 10 mph, wind direction = south / 0°, and $t = 0 \sim 300$ min): In Case A1, the ignition point and wind direction have been used in the training dataset. Therefore, AI confronts a relatively simple case that aims to show whether Model A can detect changes in different wind speed values. Nine representative periods ranging from 0 min to 300 min are demonstrated in the figures (as shown in Figure 9a). The overall trends in both simulated figures and forecasted results are similar. It is worth noting that the U-Net model has learned the burning border (the island border) throughout the process; hence the spread fits quite well near the island border. This proves that the deep learning model has grasped the spread pattern of the research area.

However, there are still some differences in the spread near

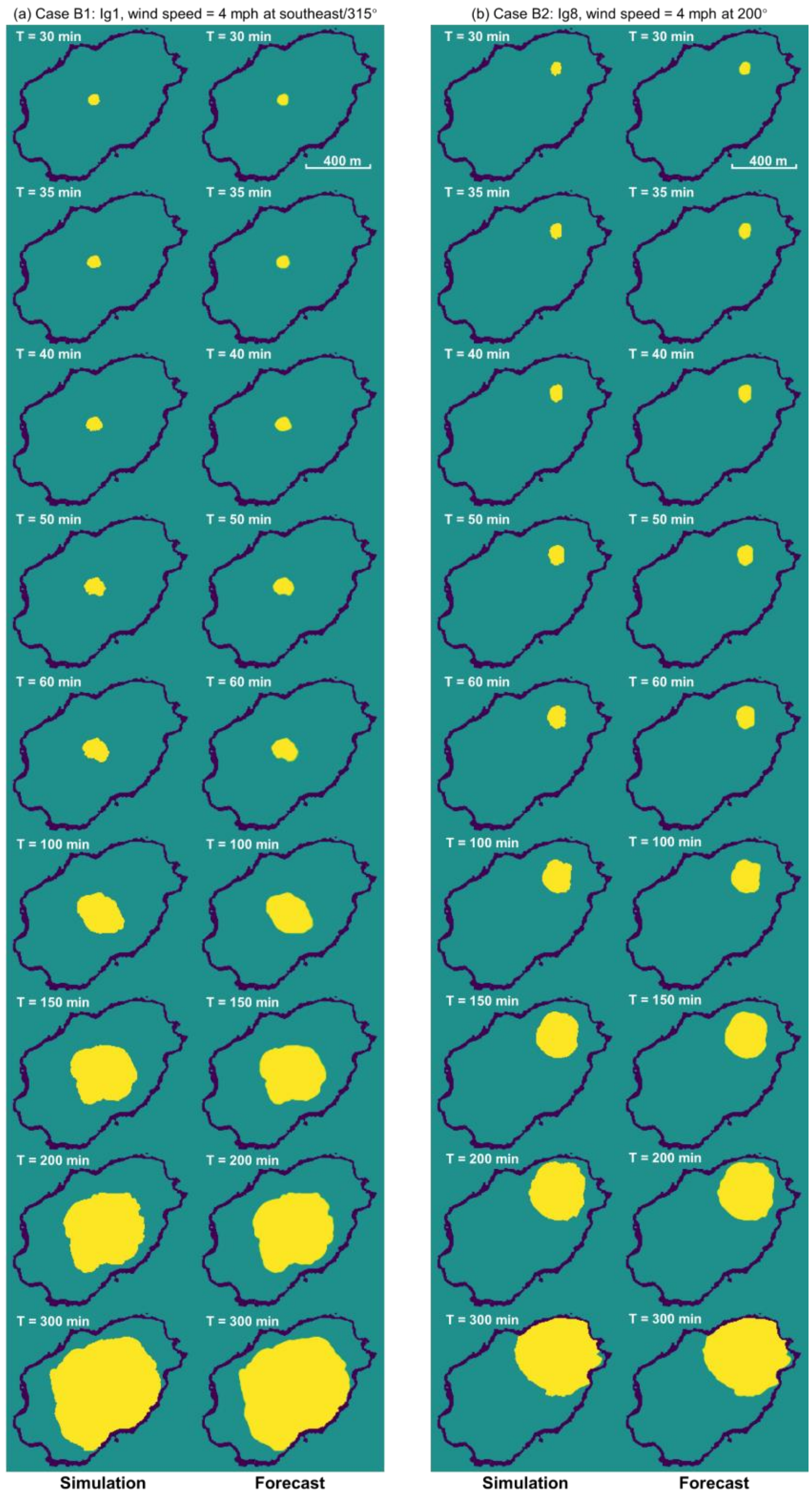

Figure 9. Forecasting results in Model A (Wildfire Hazard Assessment), (a) Case A1: Ig1, wind speed = 10 mph, wind direction = south, and $t = 0 \sim 300$ min (Videos S1), and (b) Case A2: Ig7, wind speed = 10 mph, wind direction = north by east 200°, $t = 0 \sim 300$ min (Videos S2), where input is a 12-band image.

the marginal island, where errors could be observed in both results. Regarding the figure of forecasted results at 300 min, even the middle section displays some light blue areas, which indicates that the model calculates a low possibility of it being burnt. Although some errors occur, the trained model performs well in Case A1 and shows a high tendency of successful forecasting.

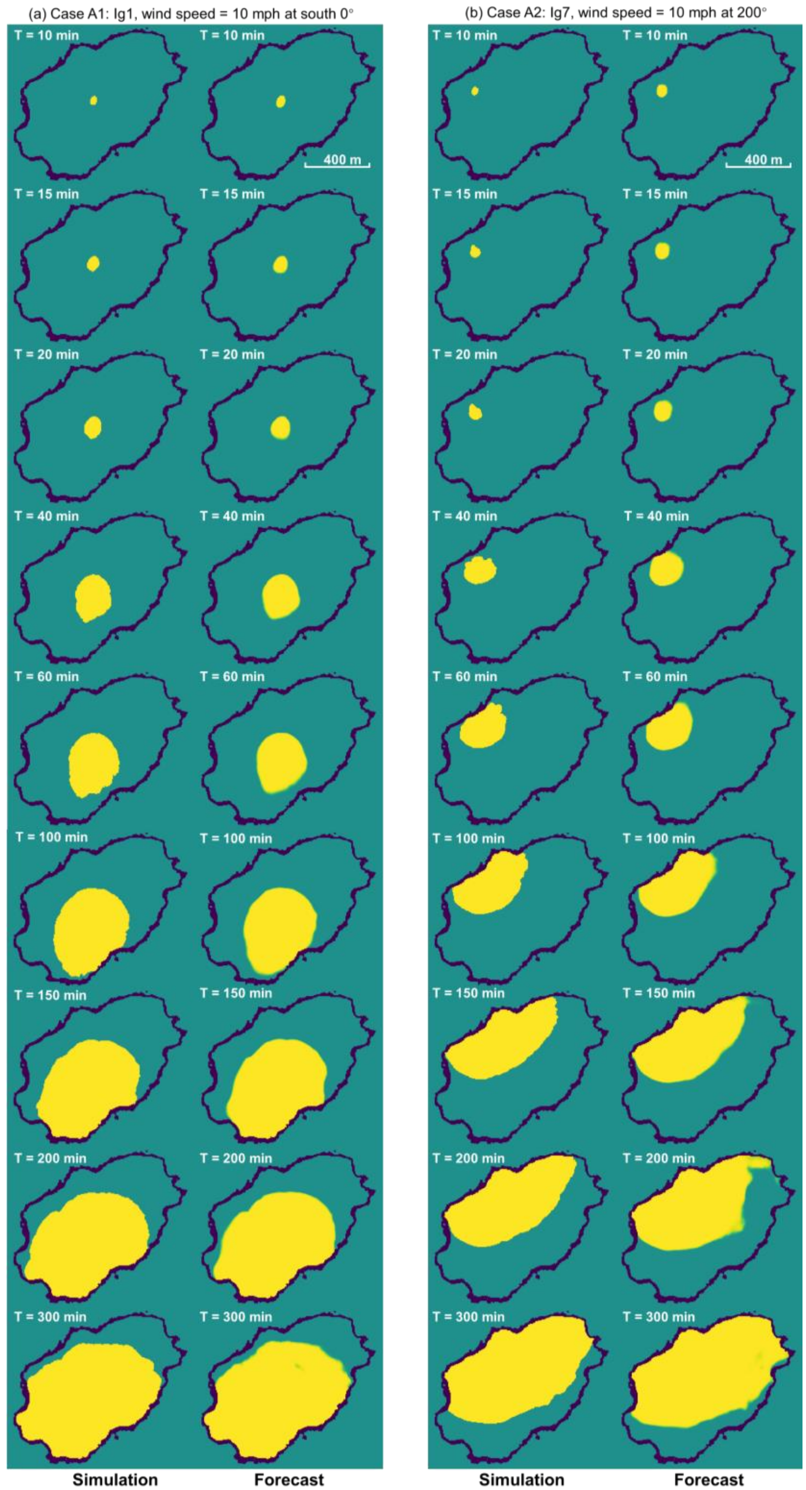

Figure 10. Forecasting results in Model B (Data-driven Wildfire Forecasting), (a) Case B1: Ig1, wind speed = 4 mph, wind direction = southeast 315°, t = 30 ~ 300 min (Videos S3), and (b) Case B2: Ig8, wind speed = 4 mph, wind direction = north by east 200°, t = 30 ~ 300 min (Videos S4), where input is five past figures.

Case A2 (Ig7, wind speed = 10 mph, wind direction = 200°, t = 0 ~ 300 min): In this case (Case A2), all the parameters are new to the model, and nine different periods ranging from 0 min to 300 min are demonstrated (as shown in Figure 9b). From 10 min to 40 min, both the forecasted and simulated figures display apparent variances, particularly near the wildfire head. The predicted results show a faster spread than the simulated ones. Although they become similar in the mid-term, after 200 min, there is a noticeable difference between the two, with the predicted burnt areas appearing to be larger than the simulated results. Additionally, there are still a few light blue regions where the AI model is uncertain whether the area will be burnt.

In summary, while the forecasted wildfire evolution figures in Case A2 did not perfectly correspond to the simulated results due to the average generalization ability of the deep learning model, the results were still considered good and acceptable. This can be attributed primarily to the random scenario chosen for the demonstration, where the model failed to comprehensively understand the burning pattern close to the new ignition site, given varying wind speeds and directions. Nonetheless, it can be concluded that AI accurately predicted the overall trends in wildfire spread when presented with a completely arbitrary scenario using Model A (Wildfire Hazard Assessment). This underscores the potential of using AI models for wildfire hazard assessment and management, particularly in situations where there is limited information or a lack of historical data. Further developments in AI and machine learning technologies may enhance these models' accuracy and generalization ability, leading to even more effective wildfire management strategies in the future.

3.3. Forecasting of Wildfire Spread in Model B (Data-Driven Wildfire Forecasting)

Model B (Data-driven Wildfire Forecasting) requires fewer input parameters than Model A and mainly relies on data-driven forecasting based on information collected by on-site UAVs. The model forecasts wildfire spread chiefly based on the previous development. In this ConvLSTM model, five consecutive maps of wildfire evolution with a 5-min time step within a 25-min interval are used to forecast the wildfire spread in the next 5 min. Thus, an entire case includes 55 spread images from 30 to 300 min. Two different fire situations are presented to demonstrate the differences between simulated and forecasted results in Model B (refer to Videos S3 and S4 for a visual demonstration).

Case B1 (Ig1, wind speed = 4 mph, wind direction = southeast / 315°, *t* = 30 ~ 300 min): In Case B1, the training dataset contained both wind direction and ignition point information. This case aimed to evaluate whether Model B (Data-driven Wildfire Forecasting) could accurately capture changes brought on by different wind speed values. Figure 10a displays nine intervals in Case B1, ranging from 30 to 300 minutes. According to the forecast, no burnt area is larger than the border, and Model B also exhibits a solid understanding of the island border. Additionally, it demonstrates good fitting results, as the fire perimeters in the two periods are relatively similar.

One minor deviation observed at the early stage of wildfire spread for Model B is that it has a slightly lower rate of spread than the simulated outcomes. This can be partially attributed to the 3 × 3 kernel size of the model, which extracts fewer features when the burnt areas are small. Therefore, the model cannot accurately forecast when the burnt area is too tiny immediately after ignition. Nevertheless, the overall forecast quality is very high.

Case B2 (Ig8, wind speed = 4 mph, wind direction = 200°, *t* = 30 ~ 300 min): In Case B2, random parameters were selected to test the generalization ability of Model B. As shown in Figure 10b, nine selected intervals were demonstrated, and despite the increased number of variables, the forecasting accuracy remained stable. Few differences were observed between simulated and forecasted results, and the rate of wildfire spread fit well with the test data. Each outcome presented many details near the wildfire head, and although there were slight disparities in the prediction, Case B2 demonstrated that Model B performed well in random scenarios.

Compared to Model A (Wildfire Hazard Assessment), Model B (Data-driven Wildfire Forecasting) exhibited better fitting and generalization abilities due to its data-driven input. Therefore, achieving highly accurate forecasted results and calibrating the results from Model A during the implementation period is feasible. The success of Model B highlights the importance of data-driven approaches in wildfire forecasting, which can help improve the accuracy and efficiency of wildfire management strategies. These approaches enable real-time tracking of fire evolution, emphasizing using UAV data, thereby providing a more accurate and comprehensive understanding of the fire dynamics.

3.4. Performance of Forecasted Results

Two models were proposed to address varying wildfire scenarios in different situations. To assess the accuracy of the

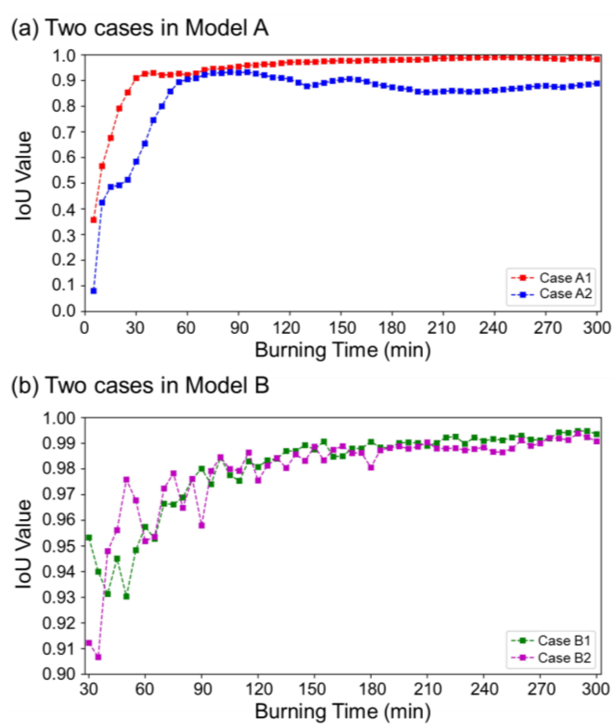

Figure 11. Evaluation of four cases, (a) two cases in Model A (Wildfire Hazard Assessment) and (b) two cases in Model B (Data-driven Wildfire Forecasting).

forecasted results compared to the simulated results, the Intersection over Union (IoU) metric was utilized. The IoU metric calculates the IoU scores of two figures at a specific burning time by dividing their intersection areas by their union areas (Zhou et al., 2019). This quantitative metric provides an objective measure for evaluating the differences between deep learning forecasts and direct simulations.

The use of the IoU metric represents a significant advancement in wildfire forecasting as it enables the accurate evaluation of the AI models' performance. By comparing the IoU scores of the forecasted and actual results, any discrepancies can be identified, which can then be used to refine and improve the models. This approach not only provides objective and quantitative measures for evaluating model performance but also helps to enhance the accuracy and efficiency of wildfire management strategies. Overall, the utilization of the IoU matrix is a valuable tool in assessing the accuracy of deep learning models in predicting the spread of wildfires (Figure 11).

Figure 11a displays the IoU values for two examples of Model A (Wildfire Hazard Assessment). The overall performance of the model is satisfying, with most values over 0.8 indicating that the spread trends are well forecasted. However, for the first six figures (before 30 minutes), the forecasted results have a low IoU value. This can be attributed to the kernel size of U-Net being 3 × 3, while the burning areas in the first 30 minutes may not extend to over 30 pixels. Consequently, the model cannot learn the spread features effectively when burnt area pixels are few, resulting in mapped wildfire evolution figures with high errors when the burnt areas are small.

On the other hand, Figure 11b shows the IoU values for two cases of Model B (Data-driven Wildfire Forecasting). The performance of the ConvLSTM model is remarkable, maintaining high IoU values throughout all 55 outcomes. In summary, the forecasted results of Model B (Data-driven Wildfire Forecasting) are very close to the simulated results compared to Model A (Wildfire Hazard Assessment). Using a data-driven approach and incorporating UAV-collected data have significantly improved the accuracy and generalization ability of the model, leading to more effective wildfire forecasting and management strategies.

3.5. Application and Future Work

The proposed dual-model deep learning method and related algorithms enable the forecasting of wildfire development based on various inputs. The forecasted wildfire scenarios can assist in planning prescribed burns, integrating real-time wildfire images obtained from UAVs to correct predictions, and providing critical information to fire services in the field, as illustrated in Figure 12.

Specifically, Model A (Wildfire Hazard Assessment) can be utilized for planning prescribed burning and predicting fire hazards under different ignition points, burning durations, and environmental conditions. The fast AI forecasting enables the exploration of many more prescribed burning scenarios to improve burning efficiency and avoid unintended wildfires. In contrast, Model B (Data-driven Wildfire Forecasting) can provide short-term wildfire spread forecasts, which can be improved by real-time wildfire images captured by UAVs.

It should be noted that these two AI models can be combined in practice for wildland fire management. For example, if extreme weather events occur, Model A could replace Model B as it performs better in cases of sudden data changes. On the other hand, Model B is more effective in wildfire spread forecasting when stable weather conditions persist. Such a dual-model forecast approach addresses the shortcomings of single-model methods without self-calibration and provides super real-time outcomes in just several seconds. Regarding the methodology itself, we assume there is no data uncertainty and potential error in the data input for our proposed AI models. Also, a huge amount of data with a high confidence level of reliability have been fed to models to eliminate the model epistemic uncertainty.

To facilitate the application of this approach, user-friendly software or even mobile applications based on our proposed AI model must be developed for firefighters. This software should combine two forecast functions - wildfire risk assessment and real-time wildfire response - automatically switching between functions based on user needs. It should also realize data fusion of all input information, such as users' drawings and images from UAVs and airplanes, to achieve the most accurate forecast without sacrificing speed.

However, multiple technical challenges are involved in developing this software, including fast and reliable data communication, edge cloud computing, image recognition of fire and burnt areas, and converting user needs into software functions. Given the dynamic nature of wildfires and potential data gaps, actual data will likely fluctuate widely. As such, we aim to enhance the stability of data collection and improve metric accuracy to minimize subjective influences. We intend to delve into the aforementioned solutions in our upcoming paper on software development based on our methodology.

4. Conclusions

This paper first introduced the development of wildfire evolution modelling and then reviewed emphatically the AI-based model in wildfire modelling and forecast. Our attention was drawn to the existing problem of forecasting the wildland fire spread relying on low-resolution satellite data and large time steps. Thus, a dual-model AI method was proposed to achieve a super real-time forecast of the 2-dimensional wildfire spread with 5-m resolution sizes and 5-min time steps. Through training, the two deep learning models developed in this study performed well in wildfire forecasting, catering to different firefighting needs. Model A (Wildfire Hazard Assessment) forecasted wildfire evolution with a 5-minute time step in 5 hours, while Model B (Data-driven Wildfire Forecasting) calibrated the forecast based on data-driven input. The novel contribution is to leverage two models which can work in tandem and be utilized at various stages of wildfire management.

In contrast to conventional simulation-based techniques

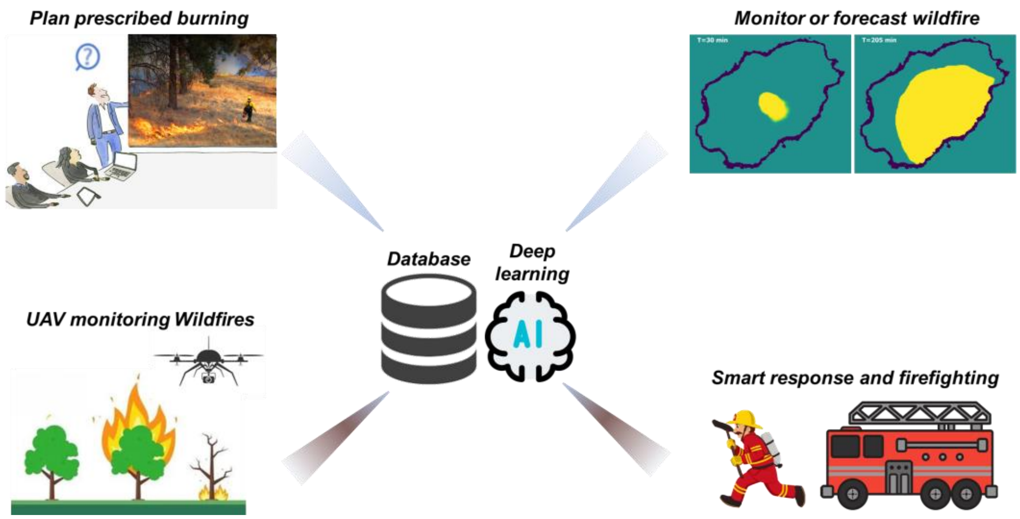

Figure 12. Future application proposal.

predominantly employed in post-incident analysis of wildfires, our approach showcases a remarkable speed enhancement of $10^2 \sim 10^4$ times in wildfire modeling and enables real-time forecasting. The entire methodology outlined in this study provides a new framework for managing small-scale wildland fires globally. More complex factors, such as actual wind distributions and broader research regions, will be added to the database in the future. Furthermore, user-friendly software for firefighting should be developed, based on the proposed deep learning models, to facilitate the usage by fire and forest services.

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