

Assessing the ability of deep learning models integrated with environmental and weather variables for predicting fire spread: A case study of the 2023 Maui wildfires

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ABSTRACT: This study aims to assess the ability of deep learning models integrated with environmental and weather variables for predicting fire spread. Different deep learning models have been proposed in the literature for predicting fire spread, but there is limited comparison of them to understand their advantages and limitations in this task. This study uses the 2023 Maui wildfires as a case study to assess five deep learning models for fire spread prediction and to compare them with a traditional fire simulation model.

KEYWORDS: Fire spread, wildfire, deep learning, Maui

Introduction

The development of accurate fire spread prediction models is important for the preparation and management of potential fire spread under different environmental and weather conditions. Predicting fire spread presents a complex challenge. This complexity arises from the effects of multiple environmental and weather factors, such as topography, wind, vegetation, and temperature (Hantson et al., 2016; Kondylatos et al., 2022). Recent studies have made great efforts in predicting fire spread using deep learning models (Burge et al., 2021; Fitzgerald et al., 2023; Huot et al., 2022; Jiang et al., 2023; Li et al., 2023; Marjani & Mesgari, 2023; Masrur et al., 2024; Masrur & Yu, 2023; Radke et al., 2019; Shah & Pantoja, 2023; Wang et al., 2023; Wu et al., 2022). A variety of deep learning models have been used, including Long Short-Term Memory (LSTM) to capture temporal variability, Convolutional Neural Network (CNN) to process spatial variability, and Convolutional LSTM (ConvLSTM) to integrate these two aspects. Moreover, research has been conducted to combine attention mechanisms with CNN or ConvLSTM, enabling models to focus on specific regions or time steps of the data. Despite these efforts, there is limited comparison of these different models for fire spread prediction to understand their advantages and limitations. The Maui fires of August 2023 were a series of major fires that affected multiple parts of Maui including Lahaina, Kula, Pūlehu/Kihei, and Olinda. Using the 2023 Maui fires as a case study, this study compares five deep learning models to understand their ability to predict fire spread.

Data and materials

This study focuses on the Maui fires but will use data from the entire state of Hawaii for model training. Fire data are obtained from NASA's Fire Information for Resource Management System (FIRMS). It provides global fire occurrence data, in the form of location points, primarily collected from NASA Visible Infrared Imaging Radiometer Suite (VIIRS). VIIRS provides high-resolution images and detects smaller-scale fires. It has a spatial resolution of 375 meters and a temporal resolution of about 12 hours. The fire data were

recorded at the center of each grid cell where a fire is detected. The attributes of the data include the latitude and longitude of a fire pixel, time of detection, and intensity of the fire in the form of Fire Radiative Power (FRP). A total of 197,567 fire points were recorded between January 20, 2012 and October 9, 2023 for the state of Hawaii (Figure 1). We exclude the data about the 2023 Maui fires and divide the remaining data into 80% for model training, 10% for validation, and 10% for testing. The 2023 Maui fire data are then added into the test set. Because the 2023 Maui fire data contain only four fires, combining it with the initial 10% test set allows a more comprehensive evaluation of model performance. Eleven environmental and weather variables are used to help predict fire spread. These variables are categorized into three groups in Table 1, which are weather, topography, and vegetation.

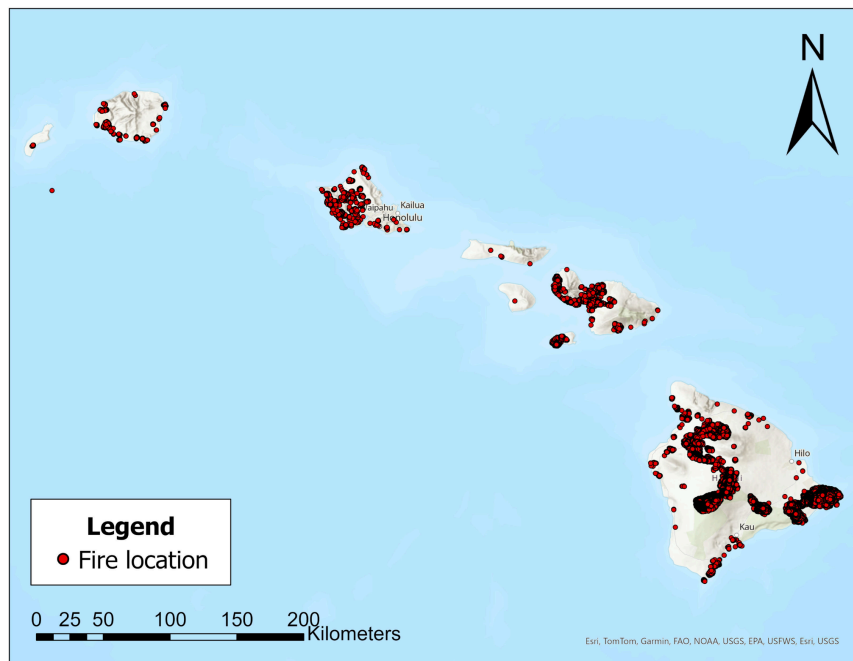


Figure 1. Fire location points for the entire state of Hawaii.

Table 1. Three categories of environmental and weather variables for predicting fire spread.

Category	Factor	Source
Weather	Temperature	ERA-5 and ERA-5 Land
	Total precipitation	
	Wind speed	
	Wind cosine direction	
	Wind Sin direction	
	Surface pressure	
	Relative humidity	
Topography	Slope	United States Geological Survey (USGS)
	Aspect	
	Elevation	
Vegetation	Normalized difference vegetation index (NDVI)	Google Earth Engine

We train and assess five different deep learning models proposed in the literature for predicting fire spread. These models are:

- LSTM: Previous studies have leveraged the LSTM model to capture temporal variability of wildfire (Liang et al., 2019; Perumal & van Zyl, 2020; Radke et al., 2019). The LSTM network (Hochreiter & Schmidhuber, 1997), a specialized form of RNN, excels in processing temporally ordered data based on its cell state mechanism. This mechanism selectively retains or disregards information over time steps.
- U-Net: Researchers have also used U-Net to predict fire spread by defining the task as a segmentation problem where the objective is to classify each cell as ‘fire’ or ‘no-fire’ (Khennou et al., 2021; Khennou & Akhloufi, 2023; Lee et al., 2020; Zhang et al., 2023). U-Net (Ronneberger et al., 2015) is a CNN based model developed for detailed image segmentation. This architecture has an encoder block that reduces and captures features of the image and a decoder block that reconstructs image details for accurate segmentation.
- U-Net with attention: Some studies have combined U-Net with the attention mechanism to enhance spatial recognition (Fitzgerald et al., 2023; Shah & Pantoja, 2023). The attention mechanism is a technique that enables models to selectively concentrate on specific parts of the input data. The merge of CNN and attention allows the model to concentrate on important areas within an image.
- ConvLSTM: Previous studies have employed the ConvLSTM model to capture both temporal and spatial variability of wildfires (Burge et al., 2021; Masrur & Yu, 2023). ConvLSTM (Shi et al., 2015) combines the features of LSTM and CNN. It is particularly useful in handling time-series data with spatial attributes. By applying convolutional operations to the hidden and cell states of LSTM, ConvLSTM can process spatial information.
- ConvLSTM with attention: More recent studies have integrated ConvLSTM with attention to focus on critical temporal and spatial features (Masrur et al., 2024). The attention mechanism selectively weighs different parts of the input sequence. It allows the ConvLSTM to focus on the most relevant patterns and temporal sequences.

Research Design

An overview of our research design is provided in Figure 2. It consists of three main steps: (1) data preprocessing, (2) model training, and (3) model comparison. For step (1), we preprocess the NASA FIRMS fire location data to extract individual fires based on the temporal continuity and spatial continuity of fire points. Temporal continuity is achieved by grouping fire data on consecutive dates, while spatial continuity is achieved using the HDBSCAN algorithm which clusters spatially adjacent fire points within each temporally continuous group. These two steps are repeated until the fire points cannot be divided into smaller groups. Individual fires are identified from the resulting fire point groups, which are then converted to images for model training and testing.

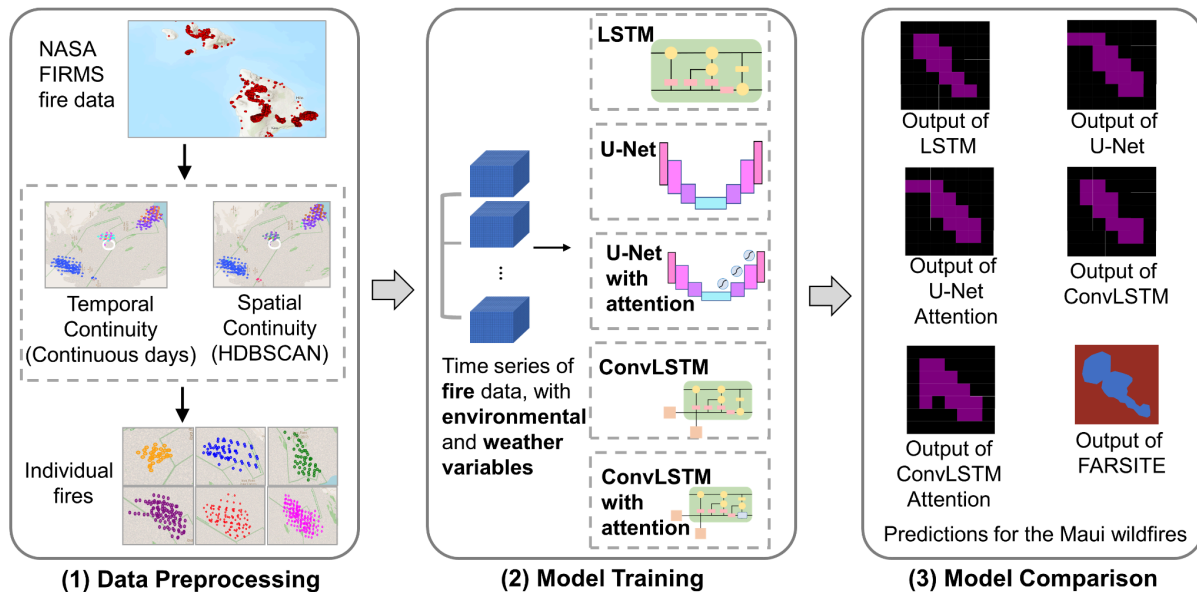


Figure 2. An overview of the research design.

For step (2), we train different deep learning models using data organized into time series. Each time step consists of fire locations and weather and environment variables in the form of images (raster data). The shape of the input will be adjusted to align with the architecture of each model. For example, for LSTM, we will reorganize the dataset by breaking down the image grid into individual cells. For U-Net and U-Net with attention, we will organize the data into one spread step per sample. For ConvLSTM and ConvLSTM with attention, we can directly use the dataset as a time series of images.

For step (3), we compare the prediction outcomes of the five different models. Metrics, such as precision, recall, and F1 score, are used to compare the predictive performance of the models. We compared deep learning models using the test set including the 2023 Maui fires. We will also compare the predictions of these deep learning based models with a traditional physics-informed fire simulation model FARSITE focusing on the 2023 Maui fires.

Preliminary results

We first compare the performance of the five different deep learning models for predicting fire spread. The metrics are measured based on whether a model has correctly predicted the pixels where the fire will spread. The results are shown in Figure 3. Overall, the two ConvLSTM models outperform other models in terms of precision, recall, and F1 score, indicating their better capability in correctly predicting fire locations while minimizing false positives. The addition of the attention mechanisms boosts performance slightly in terms of precision and F1 score but also decreases recall. This result is consistent in both U-Net and ConvLSTM. The two U-Net models overall perform worse than the two ConvLSTM models but better than the LSTM model. The input data to LSTM were broken into individual pixels, and spatial adjacency information was lost in this process. The loss of spatial information likely contributed to the lower performance of LSTM. To visualize the predictions of these models, we provide four examples in Figure 4, which shows the initial ignition fire locations,

the true fire locations in the next time step, and the predictions from the five deep learning models. The current results are preliminary, and we will further compare the outputs of these deep learning models with the output of FARSITE for the 2023 Maui fires, and will investigate the roles of the environmental and weather variables in helping make predictions.

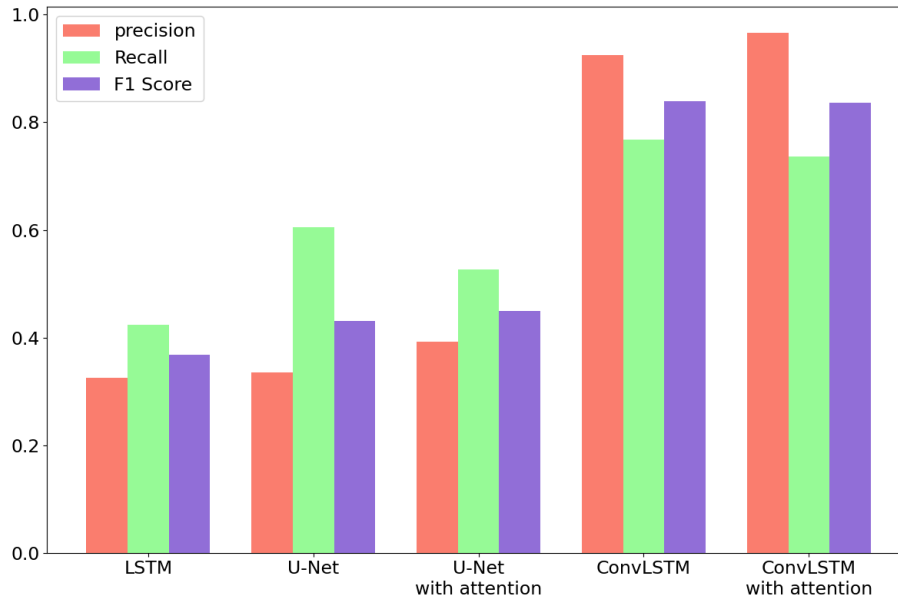


Figure 3. Performance of the five deep learning models for predicting fire spread on the test set.

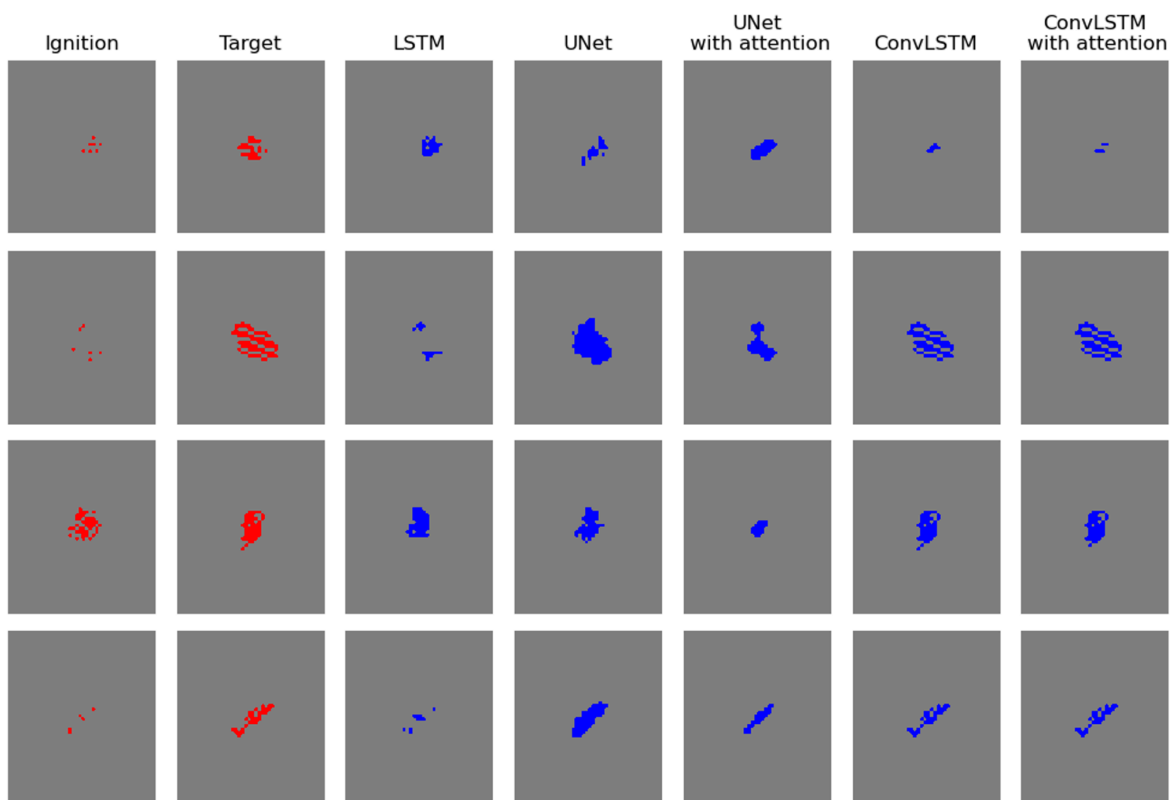


Figure 4. Examples showing the ignition fire locations, ground truth spread locations, and predicted spread locations.

Conclusions

This study aims to explore the efficacy of different deep learning models, integrated with environmental and weather data, for fire spread prediction. Our preliminary results show the potential of these models in predicting the future locations of fire spread, and they could help decision-makers prepare for fire spread and develop fire management strategies. Based on the preliminary results, we will further compare these models with a traditional fire simulation model to understand the strengths and weaknesses of different approaches.

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