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Developing Thailand Wildfire Prevention Decision Support System

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ABSTRACT

This study presents the development of Thailand Wildfire Prevention Decision Support System (ThaiWDSS) with AI-based community detection. The system assists authorities in wildfire incident management and control with focus on the residential areas. The features include the ability to predict wildfire spread, detect community areas in danger, assess damages, and simulate firebreaks. We utilized Rothermel fire spread equation and the opensource Geographic Resources Analysis Support System (GRASS GIS) while retrieving the most recent hotspot and Digital Elevation Model (DEM) from NASA's Fire Information for Resource Management System (FIRMS). We fetch wind data from external data providers, extract land cover data relevant to Thailand from Copernicus Global Land Cover Layers (CGLS) to calculate fuel models specific to Thailand based on 13 standard fuel behavior models from Landscape Fire and Resource Management Planning Tools (LANDFIRE). The users can observe the areas where fire may damage in various time frames. It also detects any community buildings in danger by a deep learning model to detect structures in the satellite images. We are able to identify temples and schools from OpenStreetMap.org because temples and schools are usually set up as shelters when it is necessary to evacuate people from the affected areas. One of the most important features of the ThaiWDSS is the capability to allow the authorities to simulate firebreaks and visualize the risks of fire spread prediction in real time. This assessment is an essence of the planning process before they make the final decision to manage such incidents. We allowed the users to experiment our proposed system using two case studies from actual fire incidents in Thailand. Preliminary comments from experts and authorities from the Royal Thai Army Air Defense Command suggest that ThaiWDSS will be a great asset during the operation as well as in the training process.

1. INTRODUCTION

Wildfires can inflict damage to a living being and natural resources whether caused by humans or naturally occurring. In Thailand, wildfires are often brought about by humans. The main cause is foraging around 62.94 %. When active fires are uncontrollable, they can spread widely and quickly propagate to community areas. Without proper preparation and protection, it can have adverse effects. Therefore, prevention measures are extremely essential. However, protection planning is a complex task and requires various pieces of information. Without complete and timely information, this may lead to inefficient planning.

In the US, WFDSS (Noonan-Wright et al., 2011) is a system developed to assist fire managers in decision-making on forest fire prevention plans. In the same way, CFFDRS (Lee et al., 2002) is the system in Canada. Other countries might have developed a system with prepared information to support fire managers. Nevertheless, there have been no systems working in this manner in Thailand. In practice, different locations in each country and weather conditions affect fire behaviors differently. Government policies, equipment, human resources, and expertise may also vary. Such a system should have features that are suitable for local areas.

The main factors affecting the spread of forest fires are geography, wind, moisture, humidity, vegetation, and other fuels. Conversely, some natural objects or structures such as water or roads may be able to stop propagating fire. Each country should focus on such details to assist the authorities in making confident decisions. Moreover, evacuation is one of the most significant measures when facing wildfire incidents in different areas. For example, when facing a disaster situation, professionals in Thailand often move people to public places such as temples, schools, or government offices. There are several challenges to the proposed system such as data preparation, wildfire spread prediction from the data, wildfire spread prediction with prevention simulation, community area identification, and damage assessment

Therefore, this study develops a decision support system for wildfire prevention in residential areas with community detection using deep learning to support officers in decision-making. ThaiWDSS consists of three main functions. The first is forecasting wildfire spread for community prevention based on weather data, fuel models, and natural firebreak. The second is indicating community areas. The last is assessing the damage to residential areas and firebreak simulation.

2. RELATED WORKS

This section reviews topics related to this study. They are research on decision support systems developed in many countries for wildfire spread prevention, forest fire spread model, building detection, and wildfire exposure to community damage assessment.

2.1 Decision Support Systems for Wildfire Prevention Management

There are developments of a system to face wildfire incidents in several countries. The common components in these systems are geographic data management, fire spread prediction, summary of information, and user interface. In the US, there is a system named WFDSS. Its first element is wildfire behavior modeling, such as flame length, rate of spread, and crown fire activity. The system in Canada named CFFDRS (Canadian Forest Fire Danger Rating System) consisted of two main components, a tool for assessing wildfire risk areas and burned area prediction. The EFFIS (European Forest Fire Information System) (San-Miguel-Ayanz et al., 2012) is a system for monitoring, planning, and assessing impacts from wildfire for European, Mediterranean regions. Every system around the world has the same functionality in many respects, fire spread prediction, data management, and active fire detection from satellites. Nevertheless, there is a further development in the community area identification in WFDSS, vulnerable places along with the economic impact assessment. This method used information collected by government agencies which may be outdated and unable to apply in Thailand. For Thailand, there is a system that displays hotspot locations like the other systems (Homhuan and Humhong, 2020), by Geo-Informatics and Space Technology Development Agency (GISDA). Nonetheless, there has been neither a system for wildfire response nor forest fire spread modeling that is suitable for Thailand's characteristics. Fire spread simulations used in other systems have been developed for the US regions. Moreover, there has not been the development of assessment of impacts on the community.

2.2 Wildfire Spread Modeling

Fire behavior has many aspects, surface fire, crown fire, underground fire, spotting fire, etc. In this study, the type of fire of interest is surface fire. One of the most well-known fire simulation programs is FARSITE (Finney, 1998). It implements the rate of spread equation by Rothermel (Andrews, 2018). This equation is widely used by wildfire spread modeling in all systems. In WFDSS, FSPro is used to model the spread of fire (Finney et al., 2011). The wildfire spread modeling consists of two main elements, the rate of spread calculation and fire perimeter modeling. It was designed based on spreading fire physical characteristics including experiments with fuel models. Furthermore, wind effects and geographical factors are also included in this equation. Necessary factors are wind speed, wind direction, fuel moisture, and fuel models. This study uses GRASS GIS (Neteler et al., 2012; GRASS Development Team and others, 2020) for wildfire prediction. This software is based on 13 Anderson Fire Behavior Fuel Models (Anderson, 1981). It is a model of fuel characteristics in the US. Besides, there is no development of fuel models for Thailand.

2.3 Building Detection

Officially recorded data of residential areas may not be up-to-date. Community areas can always change. Consequently, it is challenging to identify residential areas such as houses, schools, temples, and government offices. In the early days, building detection algorithms separated pixels of aerial and satellite images into two groups, building groups and non-building groups. This approach only considers each pixel without its neighbor.
Because of this limitation, the new way is to calculate on a group of pixels rather than each pixel. Although this method has better performance, the accuracy is still low (Mishra, Pandey and Baghel, 2016). However, different objects may be made from the same materials. For example, the roof of a building and roads may be made from concrete. As a result, their pixel values seem identical and may be understood as the same object (Luo, Li and Yan, 2021). There is an open data project named OpenStreetMap (OSM) (OpenStreetMap contributors, 2022). It provides geographic data such as road networks, water bodies, and places. ThaiWDSS uses OSM data to identify community areas vulnerable to wildfire incidents. The main data is wildfire spread prediction, population data, community areas, and infrastructure for calculating areas at risk (Oliveira, Rocha and Sá, 2021; Ager et al., 2019) proposed wildfire risk indicator. These works use the common idea to find the areas vulnerable to wildfire by identifying intersection areas of the community and predicting burned areas. Community areas are the recorded data by government agencies. Although this data is highly reliable and accurate, it may lag for years. Nevertheless, the

reality is that the residential area may change faster than the data available. This limitation may cause the assessment of the impact to be inaccurate. In addition, previous works did not consider the impact assessment related to the construction of fire protection lines. As a result, this study uses data from satellite images because it is more updated than official data. However, the next challenge is extracting building location from the images.

3. METHODS

In this section, the proposed system is explained in detail. The first subsection is an overview of ThaiWDSS including the wildfire spread model and input data. The section is building detection and the last is damage assessment. There are five subsections, an overview of the system, wildfire spread prediction, building detection, damage assessment with and without firebreak.

3.1 The Overview of ThaiWDSS

The input data are the area of interest (AOI), weather, active fire, DEM, and fuel models. ThaiWDSS solves problems with wildfire spread prediction, residential area detection, and damage assessment. As a result, the main outputs are predicted burned areas, building in community areas, and protection targets with or without firebreak locations. Visualization of ThaiWDSS is a map from OSM. In the following subsection, every part will be described in detail.

3.2 Wildfire Spread Prediction

This study adopted a forest fire simulation module in GRASS GIS utilizing Rothermel's surface fire spread equation. It is the most widely used in most systems (Sakellariou et al., 2017). The input data are original active fire positions, DEM, weather data, and fuel models. The output is a burned area vector in a selected hour after the ignition, for instance, a vector of burned area in one, two, and three hours. However, the user can select hours of fire spread prediction.

3.2.1 Active Fire Data

Active fire data may be provided by remote sensing or field collecting. Although the data from satellites is easily accessible, it might not be accurate. Hotspots data might be other heat sources rather than a real active fire, for example, factories or garbage piles. The thermal sensor's spatial resolution ranges from 300-1000 m which cannot indicate a clear position of fire. Moreover, hotspot data from the satellite may lag at least several hours behind the current situation so the user might have to input active fire data by themselves. This study uses data from FIRMS (Fire Information for Resource Management System). The data is distributed from Visible Infrared Imaging Radiometer Suite (VIIRS) on the Suomi NPP and NOAA-20, and Moderate Resolution Imaging Spectroradiometer (MODIS) on the Terra and Aqua. Latitude and longitude represent positions of initial active fire.

The positions of wildfire will be represented as points on the visualization map of ThaiWDSS and then will be used as the initial point for simulating spreading fire. They will be converted to highlighted pixels in the raster data model in AOI for making wildfire predictions. Still, the real burned areas may not exactly be in point. This is one of the limitations of spatial resolution of thermal sensing instruments on satellites. Nevertheless, it can help users to input the data when having no collecting data.

3.2.2 Weather Data

Necessary weather data is wind speed and direction in AOI. Like active fire data, users have two options to input the data. Users input the data by themselves or by importing it from various providers. ThaiWDSS can import weather data from external weather data providers. The wind condition strongly affected how the fire spread whereas weather conditions can change when the fire still keeps spreading. Conversely, the wildfire spread model supports only constant variables of weather data. Another drawback is that the weather station may be located far from the regions of interest leading to less accurate predictions. When the user has no local data, they can import public data or input the data from measurement instruments which may be more accurate.

3.2.3 Digital Elevation Model (DEM)

Another factor affecting wildfire spread is local elevation characteristics. ThaiWDSS uses DEM imported via Google Earth Engine (GEE) (Gorelick et al., 2017). The data captures an average elevation with a spatial resolution of approximately 30 meters. This data will be used to calculate slope and aspects. Slope and aspects affect the influence of wind conditions on fire spread behavior. Because the model requires terrain characteristics, this data is indispensable.

3.2.4 Fuel model

A wildfire can keep propagating as long as there is flammable material. Hence, a model of fuel is indispensable for a wildfire spread behavior (Andrews, 2018). It should cover various types of existing materials such as grassland, vegetation, and forest. Rothermel's equation implemented in GRASS GIS needs a fuel model for wildfire spread simulation. Reference (Anderson, 2981) proposed fuel model for different 13 types represented by a number ranging from 1 to 13. It was experimentally conducted based on fuel materials in North America. Table 1 shows a brief summary of the 13 fuel models.

Table 1. Summary of Fuel Model for GRASS GIS

No.	Fuel Model
0	non-flammable material
1 - 3	grassland
4 - 7	bush
8 - 10	log
11 - 13	log and litter

Non-flammable materials such as water bodies, bare ground, and also a firebreak, will be represented by zero. In practice, each fuel model is a set of many parameters for forest fire behavior calculation. Each fuel model gives a different set of variables leading to varying wildfire spread. Only if there is a fuel model for Thailand can the wildfire prediction use it. Because of this limitation, this study prepares the fuel model by roughly converting land cover data from satellite images to the fuel model. The list below shows the fuel model preparation process.

1. input AOI
2. download land cover data from GEE
3. convert landcover to fuel model

The input data is the coordinates of AOI by users. Then, ThaiWDSS will download the raster data model of land cover from the dataset, Copernicus Global Land Cover Layers (Buchhorn, 2020), via GEE. It is a global land cover dataset from satellite images with approximately 100 m of spatial resolution. The data classify land cover in each location into various types such as grassland, bare ground, vegetation, forest, urban, or water. Then, these land cover data will be converted to a raster of the fuel model. The conversion is based on documentation of the land cover dataset in GEE and details of each fuel model. The details are summarized in table 2. The result of this process will be used as a fuel model to make a wildfire spread prediction.

Table 2. Land Cover and Fuel Model Conversion

Land cover	Fuel model
unknown	3
shrubs	3
herbaceous vegetation	6
cultivated and managed vegetation	4
urban	5
bare or sparse vegetation	1
snow, ice	0
water	0
herbaceous wetland	0
moss, lichen	6
closed forest	6
open forest	5
oceans, seas	0

3.3 Building Detection

Officially recorded data of residential areas may be updated and Community areas can always change. Consequently, it is challenging to identify a building such as houses, schools, temples, and government offices.
This study uses two approaches to deal with these problems. The first method is to import public data from OSM.
House positions will be used to identify which are vulnerable to the fire and need protection. In addition, certain non-flammable structures such as roads, and water , can serve as an existing firebreak. Even though OSM can provide useful data, it is not enough because it might not be up to date. To overcome this drawback, other data is satellite images. Satellite images are more up to date data. However, it raises another problem: how to indicate accurate building positions from the images. Deep learning is one of the most popular algorithms to detect buildings from this kind of data. This study adopted a well-developed building detection project proposed on github.com/rodekruis/automated-building-detection (Margutti and De Jong, 2022). This project presented automated building detection from the images downloaded from Bing Maps (Microsoft Corporation, 2022). The contributors of this project provided a pre-trained deep learning model including other useful tools. Thus, these data will be used to find the location of buildings exposed to wildfire incidents and also displayed on the visualization map along with OSM data.

3.4 Assessing Wildfire Damage to Community Areas

Assessing the impact is challenging. Different definitions of damage lead to a variety of damage assessment methods in many studies. In this study, we define the damages as the number of buildings in predicted burned areas. As a result, the quantity of damage is calculated by counting the number of intersection vectors of predicted burned area and detected building. Nonetheless, the accuracy of the building detection model leads to the performance of detected damage assessment. The damage assessment is calculated without any protection and shows the possible extent of the fire hazard affected.

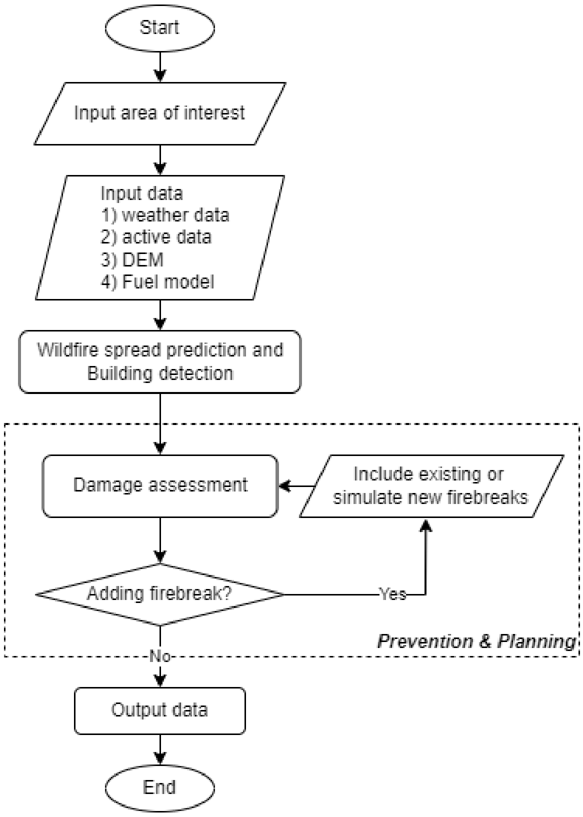

Figure 1. Application Process

3.5 Damage Assessment with Firebreak

The user can use this application by the diagram summarized in Figure 1. After getting the damage assessment from the previous subsection, the next step is to make prevention using firebreak. ThaiWDSS provides tools for the user to draw simulated firebreaks. Each simulated firebreak will be used to change the fuel model at its locations to represent non-flammable material rather than flammable material. As a result, when starting a new wildfire spread prediction, the result will not show the burned area where the firebreak is located. Moreover, reducing burned areas also decreases the damage. Differently drawn firebreaks result in a variety of wildfire spread directions and damage. We assume that the prevention objective is minimum damage although in practice there might be many constraints such as response time, instrument, and human resources. The user can simulate different firebreaks to compare the damage until the user can make the best decision.

4. RESULTS

This research uses two study areas. Both had experienced wildfire incidents near the community. The first is in Mueang Nakhon Nayok District, Nakhon Nayok province The second study area is in the Samoeng Tai sub-district, Samoeng District, Chiang Mai province. The terrain is mountains and rocky cliffs, making it difficult to carry out fire prevention. Table 3 summarizes preliminary data for each study area including the initial fire locations and weather data.

Table 3. Weather Data Summary

Study Area	1	2
temperature	30	33
humidity	40	41
wind speed (kmph)	13	4
wind direction (degree)	102	211

Because there is no locally recorded initial burned areas and weather data, we use public weather data and hotspots from FIRMS. The weather can always change, but wildfire spread prediction does not support weather change. The prediction results will be on the conditions that the weather has not changed. As a result, the prediction in longer hours leads to a decrease in accuracy. For instance, the predicted burned area in four hours is more reliable than eight hours. One of the most crucial wildfire spread factors is fuel moisture. However, there is no available data so this study uses fixed fuel moisture at 20 %. Figure 2 illustrates the predicted burned area in 8, 16, and 24 hours since initial active fires in red, orange, and yellow respectively. The residential area is displayed in the pink polygon. In the first study area, the community area will be on fire in 16 hours if there is no protection. Moreover, some houses will be affected in 24 hours but these are not the most urgent ones. Counting the number of pink polygons intersected with the burned area will give the number of houses in danger. This number is useful to estimate the impact. To prevent imminent damage, one approach to do so is to construct a firebreak in the right position. In figure 3, the blue line is drawn by the user and it represents the location of the fire break. Then, the user starts wildfire prediction and damage assessment again. The result shows that the predicted burned area will not cross the fire break. Additionally, community areas at risk are not intersected with the burned area. In figure 2, the number of houses at risk is 26 while it is 0 in figure 3.

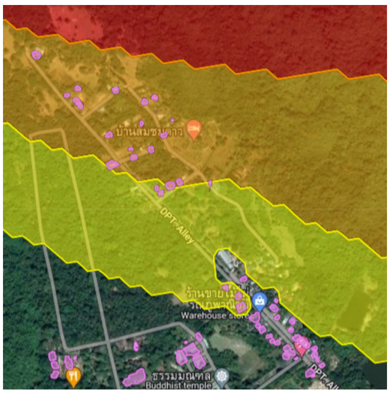

Figure 2. Study Area 1 without Firebreak

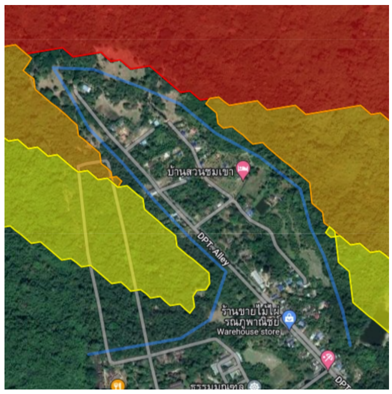

Figure 3. Study Area 1 with Firebreak

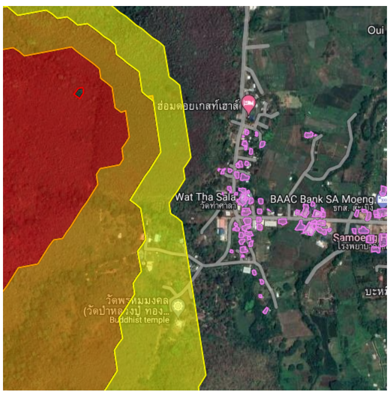

Figure 4. Study Area 2 without Firebreak

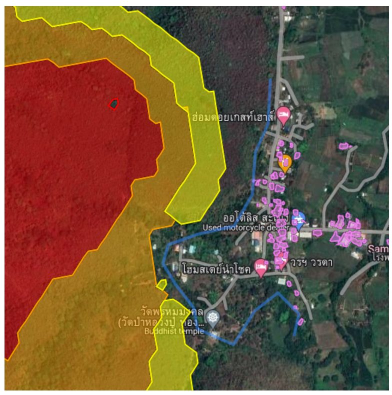

Figure 5. Study Area 2 with Firebreak

In the second study area, in figure 4, the wildfire ignition is in the mountains. The community lies in the east of the mountains. From the simulation, the community may not be on fire in 24 hours. However, there are still three houses in the center of the figure that will be affected. The protection of the community leads to safety shown in figure 5.

Another point is that the extent of the firebreak virtually drawn by the user might cause an error in a predicted burned area. The reason is that all data for the wildfire prediction model is a raster data model with a specific resolution. The data used to represent the firebreak is a fuel model converted from land cover data.The land cover data has a resolution of 100 m. Still, a firebreak that is constructed in practice might be like a dirt road with a width of 2-5 m. The width of the firebreak is much smaller than the resolution of the land cover data. Hence, some pixels of land cover raster data could not represent the line of firebreak correctly. To overcome this problem, ThaiWDSS provides two approaches. The first is that the system uses a constant firebreak width of 10 m when the user draws a line of firebreak. Another way is to allow the user to draw a polygon of firebreak but it has to be much bigger than usual to avoid errors.

5. CONCLUSION AND DISCUSSION

This study introduced an attempt to develop the decision support system for wildfire prevention in Thailand. ThaiWDSS aims to be a tool for supporting firebreak planning. The first problem is to forecast fire spread direction. We presented a way to overcome this limitation by converting satellite data. Even if there is no detailed information on fuel materials, this approach can give a helpful fuel model for wildfire spread prediction. One way to improve the model for Thailand is to develop a fuel model for Thailand. This might be very beneficial for this field of study. Another important factor that contributes much impact on wildfire spread behavior is humidity and fuel moisture. Fuel moisture causes the extent of burned area and also the rate of propagation. Even though this data is required by the model, it is out of the scope of this research. Thus, the purpose system uses constant fuel moisture at 20 %. Moreover, it is not easy to collect data when facing an actual fire incident. This problem can be a further research topic.

The next problem is building detection. This word adopted a well-developed project to include in ThaiWDSS. In the field of computer vision, there are many studies on building detection from satellite images using deep learning. To develop ThaiWDSS, we hope that a building detection algorithm might help give more residential areas. Official data may be outdated and will be used with detected algorithms. As a result, one solution is to improve building detection algorithms from a satellite image. We expect that the model can give a more useful location for the community area. Nevertheless, some buildings are not detected accurately. The real aim of the implementation of building detection algorithms is to prepare the residential area that would be a target of fire hazards. In practice, it is possible to collect residential areas in the area with a high probability of fire incidents for future events. Nevertheless, when a fire incident occurs in a region with no prepared information on community location, both the building detection algorithms and online data might be helpful. Moreover, the damage assessment approach is another aspect to be developed. The different definition of damage from wildfire leads to variations in the implementation of damage assessment. This study defined damage of wildfire incidents as the number of houses in danger so we adopted damage assessment by counting detected buildings in predicted burned areas. When it comes to prevention methods, the main focus of ThaiWDSS is firebreak simulation. The user can draw a firebreak geometry on the map for damage assessment when planning prevention operations. Nonetheless, ThaiWDSS testing results show that it could be helpful in the actual event.

This study aims to develop a system that can support one aspect of wildfire prevention, firebreak construction location. We hope this study will lead to future studies on the development of the decision support system for Thailand. This study was conducted without real use by experts because there is another task. It is to evaluate the wildfire spread model, however, it is still in progress.

6. ACKNOWLEDGEMENT

This study cannot begin without many open-source projects contributed by the number of developers. One of the most important is automated-building-detection on www.github.com. Moreover, many data providers such as Weatherapi, FIRM, Bing Maps, and GEE are indispensable. In addition, this study cannot be conducted without a good recommendation from experts who have experience in wildfire prevention. Map data copyrighted OpenStreetMap contributors and available from https://www.openstreetmap.org.

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