MACHINE LEARNING APPLICATION IN RESPONSE TO DISASTER RISK REDUCTION OF FOREST AND PEATLAND FIRE

Impact-Based Learning of DRR for Forest, Land Fire, and Peat Smouldering

APLIKASI PEMBELAJARAN MESIN UNTUK PENGURANGAN RISIKO BENCANA KEBAKARAN HUTAN DAN LAHAN GAMBUT

Pembelajaran Berbasis Dampak pada Pengurangan Risiko Bencana untuk Kebakaran Hutan, Lahan, dan Smouldering Gambut

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Abstract

Peat forest is a natural swamp ecosystem containing buried biomass from biomass deposits originating from past tropical swamp vegetation that has not been decomposed. Once it burns, smoldering peat fires consume huge biomass. Peat smoldering fires are challenging to extinguish. These will continuously occur for weeks to months. Experts and practitioners of peat smoldering fires are the most recommended effort to prevent them before they occur with the strategy: 'detect early, locate the fire, deliver the most appropriate technology.' Monitoring methods and early detection of forest and land fires or 'wildfire' have been highly developed and applied in Indonesia, for example, monitoring with hotspot data, FWI (Fire Weather Index), and FDRS (Fire Danger Rating System). These 'physical simulator' based methods have some weaknesses, and soon such methods will be replaced by the Machine Learning method as it is developing recently. What about the potential application of Machine Learning in the forest and land fires, particularly smoldering peat fires in Indonesia? This paper tries to answer this question. This paper recommends a conceptual design: impact-based Learning for Disaster Risk Reduction (DRR) of Forest, Land Fire, and Peat Smouldering.

Keywords: Artificial Intelligence; Machine Learning; Wildfire; Peat Smouldering; DRR impact-based

Abstrak

Hutan gambut adalah ekosistem rawa alami, di dalamnya tertimbun biomassa yang berasal dari vegetasi rawa tropis masa lalu yang belum terdekomposisi. Jika terbakar, kebakaran smouldering gambut bawah permukaan mengkonsumsi biomassa dalam jumlah yang cukup besar. Kebakaran gambut smouldering ini sangat sulit dipadamkan, dan akan terus berlangsung hingga berminggu-minggu bahkan berbulan-bulan. Upaya yang dianjurkan oleh para ahli dan praktisi kebakaran smouldering gambut adalah mencegahnya sebelum terjadi dengan strategi: 'detect early, locate the fire, deliver the most appropriate technology'. Metode pemantauan dan deteksi dini kebakaran hutan dan lahan sudah sangat berkembang dan sudah diterapkan di Indonesia, misalnya pemantauan dengan data hotspot, FWI (Fire Weather Index), dan FDRS (Fire Danger Rating Sistem). Metode berbasis 'simulator fisik' ini memiliki kelemahan dan perlahan tapi pasti metode ini akan tergantikan dengan metode pembelajaran mesin sebagaimana yang tengah berkembang saat ini. Bagaimana dengan potensi penerapannya di bidang kebakaran hutan dan lahan (karhutla), khususnya kebakaran gambut smouldering di Indonesia? Paper ini mencoba untuk menjawab pertanyaan ini sekaligus merekomendasikan sebuah konseptual desain: Pembelajaran Berbasis Dampak pada Pengurangan Risiko Bencana (PRB) Karhutla dan Smouldering Gambut.

Kata Kunci: Kecerdasan Buatan; Pembelajaran Mesin; Karhutla; Smouldering Gambut; Impact-based PRB

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INTRODUCTION

Peat forest is a natural swamp ecosystem containing biomass originating from past tropical swamp vegetation that has not yet been decomposed. If peat swamp forest is drained by draining the water to convert the land use into Industrial Forest Plantation (i.e., Hutan Tanaman Industri), plantations, and agriculture, it will further cause the forest fire. The accumulation of peat biomass in this ecosystem, which was initially submerged in water, is exposed to the surface and is prone to the dangers of a forest fire, either from the ignition or by fire when the peat deposits on the surface begin to dry up, especially in the dry season. When a fire occurs in the peat ecosystem, two biomass fires take place, namely: (1) Open flame (surface fire), which consumes 5 kg/m^2 of biomass, and (2) Smouldering peat fire (subsurface peat fire) consuming 75 kg/m^2 of peat biomass or 15 times larger than the open flame[1)] (Figure 1).

Figure 1.
Mechanism of forest and peatland fires: *Open flame* and *Smouldering* [1,2)]

Smoldering or subsurface peat fires are highly interested in the global community of forest and shrub fires - IAWF (International Association of Wildfire). Smoldering is seen as a global fire phenomenon dominated by the occurrence of 'mega-fires of peatlands.' Such largest fire disaster has hit the world and is difficult to extinguish except by extreme rain. IAWF magazine published in April-June 2014 declared that peat fires ' smoldering' is a global phenomenon. Specifically, a synopsis and a paragraph were written as follows[3)]:

> *"From Indonesia to Botswana, from Scotland to North Carolina, peat mega-fires burn for months, destroy habitat, clog the air with haze, and self-accelerate climate change impacts*."
>
> *"Peat soils are made by the natural accumulation of partially decayed biomass and are the largest reserves of terrestrial organic carbon. Because of this vast accumulation of fuel, once ignited, smoldering peat fires burn for very long periods of time (e.g., months, years) despite extensive rains, weather changes, or firefighting attempts. Indeed, smoldering is the dominant combustion phenomena in mega-fires of peatlands, which are the largest fires on Earth."*

Smoldering is the peatland fire phenomenon, causing haze in Southeast Asia and Northeast Europe, which is the biggest fire disaster in the world[4)]. Therefore, along with developing research on climate change mitigation, research on smoldering is also increasingly emerging. In the field of wildfire science and management, the Machine Learning (ML) method has developed very fast. A review of 298 papers in various journals and proceedings was done with ML applications in this field, from 1996 to 2019[5)]. This study provides an overview of widespread development trends, reaching into 20 application domains. It is indicated that the most developments occurred in the Fire Occurrence, Susceptibility, and Risk cluster (50%), followed by Fire Detection and mapping (15%), Fire Behaviour Prediction (13%), and 3 other clusters with less than 10% number of papers, namely Fire effect, Fire Weather and Climate Change, and Fire Management (Figure 2). How potential is the application of ML in the field of forest and land fires, particularly in response to disaster risk reduction (DRR) of forest, land fires, and peat smoldering in Indonesia? This paper attempts to answer this question through the following subjects:

- State of the art machine learning in forest and land fires management;
- Outlook on DRR technology of forest and land fires by BPPT, and opportunities for ML implementation;
- Impact-based forecasting (IBF) and machine learning for DRR technology of forest and land fires;
- Recommendations: ML and IBF on DRR of forest fire and pet smoldering.

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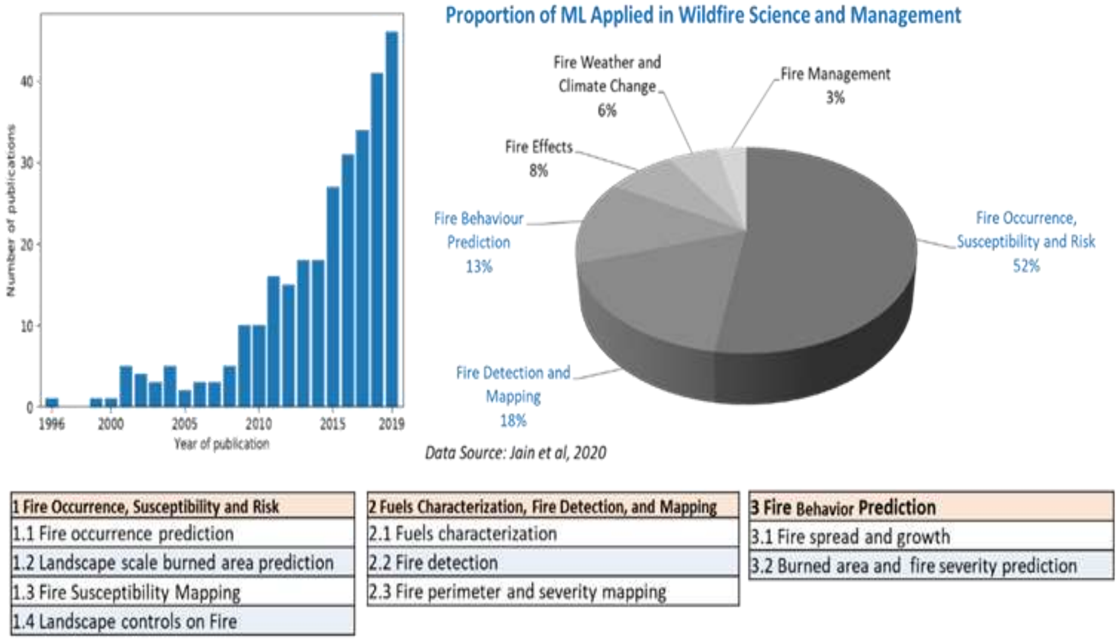

Figure 2.
Number of Publications between 1996 and 2019, and Application Proportion in 6 Domain Clusters of Wildfire Science and Management[5)]

STATE OF THE ART MACHINE LEARNING IN SCIENCE AND MANAGEMENT OF FOREST AND LAND FIRE

The current state of the art prediction modeling of forest fires includes a physics-based simulator. Firefighters and their strategic planners rely on making critical decisions to allocate limited firefighting resources in the case a fire occurs[6)]. However, these physics-based simulators have disadvantages such as (1) their accuracy is very low, (2) they have a predictive bias in the area in which they are designed to be used, (3) they are often difficult to design and implement because they require a large number of expert rules, (4) involving many variables, complex, and heterogeneous data format.

On the other hand, a Machine Learning algorithm learns its own parametric rules directly from the data. It does not require an 'expert rule,' so that it had its own advantages when the number of parameters used becomes larger and its physical properties becomes more complex such as in the event of forest and land fire. Therefore, a machine learning approach to forest and land fire preparedness and response can reduce the limitations of physical simulators.

Therefore, the science and management of forest and land fires depend heavily on developing empirical and statistical models for meso-scale, synoptic, strategic, and global scale processes[7)], where the utility depends on their ability to represent complex and non-linear relationships between variables, and also depending on data quality and availability. Furthermore, recent developments of the ML algorithm, with a particular focus on extracting spatial features from images, have led to a sharp increase in the adoption of Deep Learning (DL) in the last decade.

Taxonomy of Machine Learning Method and Popular Algorithm for forest and land fire

There is a compilation of taxonomic systematic which is expected to be used as a general guide for forest and land fire scientists interested in applying the ML method in science and management of forest and land fires[5)]. In general, there are three typologies of the ML method that are popular and have been applied in various domains of science and management regarding forest and land fire: (1) supervised learning; (2) unsupervised learning; and (3) agent-based learning, the details of which are presented in Table 1.

Table 1.

Popular Method and Algorithm of Machine Learning for Forest and Land Fire

ML TYPE	APPROACH	DATA	TASK	DOMAIN	POPULAR ALGORITHM
Supervised	Map labelled input	Continues	Regression	Fire susceptibility	NB, DT, CART, RF,
Learning	to known output			Fire Spread/Burn area prediction	DNN, GP ANN, GA,
				Fire occurence	RNN, MAXENT,
				Fire severity	CA,MLR, GLM, GAM
				Smoke Prediction	
				Climate Change	
		Categorical	Classification	Fuels characterization	ANN, DT, BRT, RF,
				Fire Detection	KNN, SVM, K-SVM, LR,
				Fire Mapping	LDA
Unsupervised	Understand	Target	Clustering	Fire Detection	KM, SOM,
Learning	patterns and	variable not		Fire mapping	autoencoders, GMM,
	discover output	available		Burned area prediction	ISODATA, HMM, HC,
				Fire weather prediction	PCA, DBSCAN
			Dimensionality	Landscape controls on fire	SOM, autoencoders, t-
			Reduction	Fire susceptibility	SNE, RF, BRT, MaxEnt,
				Fire Spread/Burn area prediction	PCA, factor analysis
Agentbased	Single or multiple	Reward based	Optimization	Optimizing fire simulators	GA, MCTS, A3C
Learning	agents interact	rather than		Fire spread and growth	
	with environment	target action	Decision	Fuel treatment	DQN, A3C, MCTS
			Making	Planning and Policy	
				Wildfire response	

A3C Asynchronous Advantage Actor-Critic
AdaBoost Adaptive Boosting
ANFIS Adaptive Neuro Fuzzy Inference System
ANN Arti_cial Neural Networks
ADP Approximate Dynamic Programming
Bag Bagged Decision Trees
BN Bayesian Networks
BRT Boosted Regression Trees
BULC Bayesian Updating of Land Cover
CART Classi_cation and Regression Tree
CNN Convolutional Neural Network
DNN Deep Neural Network
DQN Deep Q-Network
DT Decision Trees
EDT Ensemble Decision Trees
ELM Extreme Machine Learning
GA Genetic algorithms
GBM Gradient Boosted Machine
GMM Gaussian Mixture Models
GP Gaussian Processes
HCL Hard Competitive Learning
HMM Hidden Markov Models
ISODATA Iterative Self-Organizing DATA algorithm
KNN K Nearest Neighbor
KM K-means Clustering
LB LogitBoost (incl. AdaBoost)
LSTM Long Short Term Memory
MaxEnt Maximum Entropy
MCMC Markov Chain Monte Carlo
MCTS Monte Carlo Tree Search
MLP Multilayer Perceptron
MDP Markov Decision Process
NB Naive Bayes
NFM Neuro-Fuzzy models
PSO Particle Swarm Optimization
RF Random Forest
RL Reinforcement Learning
RNN Recurrent Neural Network
SGB Stochastic Gradient Boosting
SOM Self-organizing Maps
SVM Support Vector Machines
t-SNE T-distributed Stochastic Neighbor Embedding

Adopted from Jain et al 2020

Top Three Machine Learning Algorithm in Science and Management of Forest and Land Fire

Table 1 identifies the most widely used ML methods in each domain in the science and management of forest and land fires. There are 3 methods of ML that are most widely used, namely (1) Random Forest; (2) Maximum Entropy; and (3) Artificial Neural Network (Figure 3). These three methods are briefly described in the following sub-section.

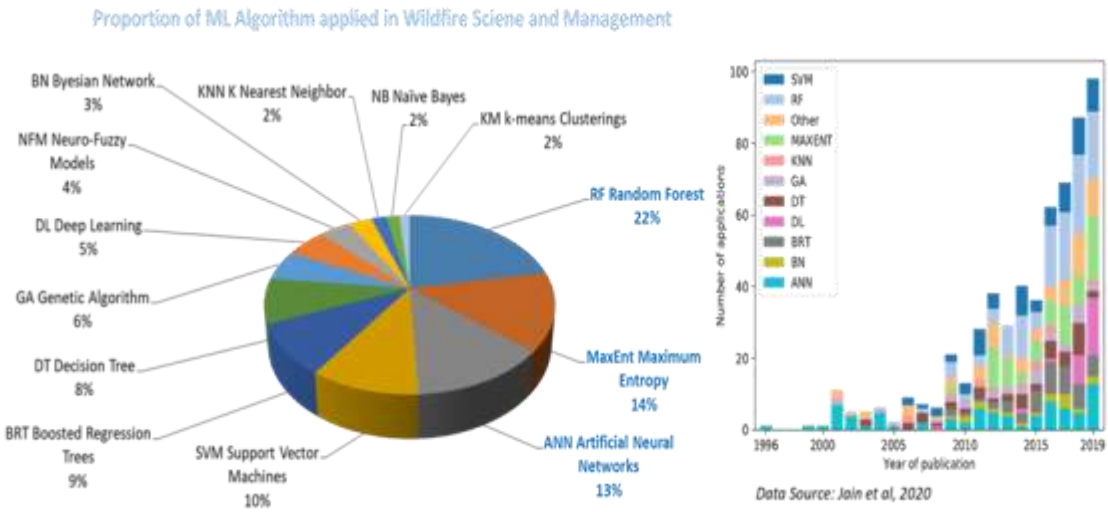

Figure 3.
The Most Used Machine Learning Algorithm in Forest and Land Fire Application

Decision Tree dan Random Forest

In the taxonomy system (Table 1), a Decision Tree (DT) is a part of the supervised learning algorithm. DT can be used to solve classification and regression problems (classification and regression), using a set of if-then-else rules as decision nodes that form a decision tree's decision tree, ending in leaf nodes or terminal nodes. Each branch results from certain decisions made by the algorithm, while leaf nodes are the output of a decision tree model. DT can be used for classification problems using labeled data and continuous value for regression problems.

Random Forest (RF) consists of several decision trees. The structure of a decision tree is shown in Figure 4. Basically, each tree consists of many branches connected by several decision nodes connected continuously to reach the end node (terminal node). At each decision node, the tree will be divided into different branches. Each of these nodes will select features randomly and also select the data set as training data randomly with a replacement where the selected data can be randomly selected again in the next tree formation.

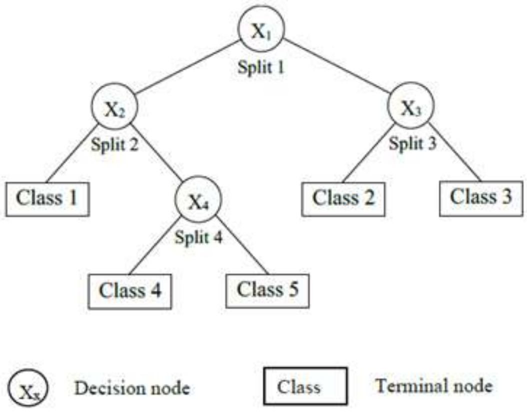

Figure 4.
Structure of a decision tree[8)]

In practice, RF is an ensemble model that produces many classification models and combines the results obtained[9)]. In this case, RF consists of many individual DTs that make up a forest, which can be used for classification and regression modeling. In classification modeling, RF determines a class's final result based on the majority voting of all the decision trees built[10)]. In regression modeling, RF sets the final value based on the average value of all trees' outputs. For example, in modeling the classification of satellite images, from the 500 trees built, the results show that 400 trees indicate the value of a pixel is forest class, while 100 trees are shrubs. The modeling results conclude that the pixel value is the forest by the largest vote. On the other hand, regression modeling is the average result of the overall predictions. In RF modeling, each data set is randomly taken in each tree, where 36% of the data set is used for error estimation of the prediction results, and the rest is used for training data[9)].

Artificial Neural Networks and Deep Learning

Artificial Neural Network (ANN) is a supervised learning method. This method is an information processing that is inspired by the mammalian brain nervous system's procedure, consisting of a huge number of processing elements (neurons) that are interconnected and working together to answer certain problems through the learning process of simple associations for information processing.

A neuron (so-called a perceptron unit or logistic) is the elementary unit of an Artificial Neural Network (ANN). Neurons have a set of inputs that are combined linearly by multiplying the weight associated with the input. The final weighted number forms the output signal, which is then passed through a (typical) non-linear activation function. Some activation functions are the sigmoid, tanh, and the Rectified Linear Unit (ReLU). This non-linearity is important for general learning because it creates a cut-off (or threshold) between positive and negative signals. The weight on each connection represents a suitable function parameter using supervised learning by optimizing the threshold to reach the maximum differentiation value[5)].

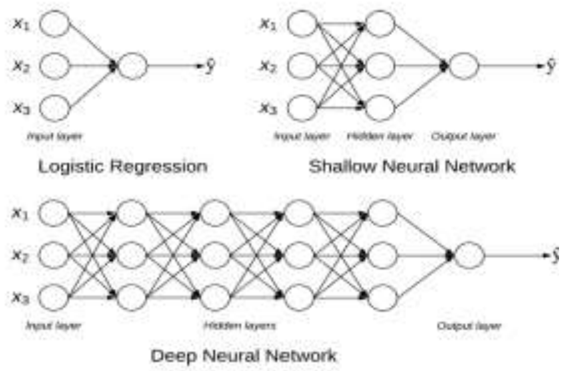

Figure 5.
Artificial Neural Network (ANN): Logistic Regression (LR) as 'building block,' Shallow Neural Network (NN with 'one hidden layer'), and Deep Neural Network[5)]

The building block of an ANN is Logistic Regression (LR), which does not have a "hidden layer" and a "sigmoid activation function." An ANN can be formed by an LR with at least one 'hidden layer' having various sigmoid activation functions. Deep Neural Networks (DNN) have more 'hidden layers' with optimization methods to increase training data (Figure 5).

The most popular method of machine learning, deep or not, is supervised learning. For example, suppose we want to build a system that can classify an image containing a house, car, person, or pet. The first thing to do is collect "big data" of pictures of houses, cars, people, and pets, each labeled with its category. Then the 'machine' is given training by providing an image of the labeled 'big data' to produce the output in a score vector, one vector for each category. This score vector assigns a classification based on the score value from highest to lowest of all categories.

Bayesian Networks and Maximum Entropy

Bayesian networks (BN) are popular algorithms in many application domains because they use an intuitive graphical language to determine probabilistic relationships between variables. This technique can also be used to calculate the probability of its output[11)]. BN uses the basis of Bayes' theorem, which is 'causal reasoning,' where the relationship is defined as correlational instead of causal to fit parameter automatically from the data model to represent the model data itself.

Maximum Entropy (MaxEnt) is the only framework that fits a spatial probability distribution by maximizing entropy, reliable with current knowledge[12)]. MaxEnt is considered a Bayesian method due to its compatibility with Bayes Theorem application as current knowledge corresponds to specifying former distribution. MaxEnt has widely used in the modeling of landscape ecology species distribution[13)], in which knowledge on the occurrence observations of particular species is known.

Machine Learning Method Development in Science and Management of Forest and Land Fire

Forest and land fire are one of a series of complex ecosystem dynamic processes. Its events and behavior are the interaction product of several interconnected factors, namely ignition sources, composition and type of fuel, weather, topography, and landscape configuration. A brief description is presented here regarding ML application's development and trends in various domains of forest and land fire science and management, particularly those that have experienced rapid development in the last decade[5)].

Fire Occurrence Prediction

Early development of the Fire Occurrence Prediction (FOP) model was known since the early 1920s[14)]. The pattern of fire occurrence is inherently random. Therefore, stochastic and statistical models that incorporate random variables into their structure are natural for modeling wildfire occurrence[15)]. FOP models typically use a regression method to relate response variables (fire reports or hotspots) to weather, lightning, and other covariates for geographic units or spatial probabilities.

The ML method most commonly used in studies to predict fire occurrence is ANN (Artificial Neural Network). After 2012, RF (Random Forest) became more popular for FOP. The maximum entropy (MaxEnt) method is also used to predict fire events. The most recent development of ML application for forest and land fires is big-data combined with unsupervised and supervised ML collaboration using a 2-stage learning method. Some studies are using ML for fire occurrence prediction can be found[16-19)].

Burnt Area Prediction

Compared to other domains, the ML method in studying the burnt area prediction model is still relatively new. However, it has involved various ML methods. Also, a combination of ML and non-ML methods are used in this domain. Various studies in this field using ML can be found in some studies[20-22)].

Susceptibility and Risk Mapping of Forest and Land Fire

The approach method commonly used for susceptibility mapping is modeling forest and land fire hazards using remote sensing data or data from respected institutions, combined with explanatory variables such as landscape, climate, structure, and anthropogenic variables. A variety of modeling approaches used are MaxEnt, BRT, or RF. A summary of the status and progress of ML methods and algorithms in the susceptibility mapping and hazard mapping domains be found in some studies[23-25)].

Landscape Modelling as A Control of Forest and Land Fire

Many ML methods used in the forest and land fire susceptibility mapping model are also used in the land fire control model. Important variables for hypothesis formulation and testing or construction of forest and land fires models are weather, vegetation, topography, structural, and anthropogenic. The most common methods used in this domain are MaxEnt, RF, BRT, and ANN. In general, the drivers or controls for the occurrence of a fire or burnt area are widely varied according to the study area's spatial size and the methods used. On a regional and global scale, climate variables are the main driver of forest and land fires. While on a smaller scale, the main driving factor is

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anthropogenic or landscape structural factors. Several papers focus on the diversity of results for more demanding issues and spatial scales (global, country, ecoregion, urban)[26-29].

Machine Learning Model for Fuel Type Characterization

Fire behavior, including fuel consumption, spread rate, and intensity, is related to the living and dead condition properties, which include moisture content, biomass, and vertical and horizontal distribution. All fire behavior models require fuel properties as input, whether it is a simple category of vegetation type as in the Canadian FBP System or as physical properties in 3-dimensional space (e.g., FIRETEC model). Research on the fuel properties prediction has been conducted at two different scales 1) regression applications to predict quantities such as single-tree crown biomass from more easily measured variables such as height and diameter and 2) classification applications to map fuel type or quantity of fuel above the landscape from the visual interpretation of aerial photographs or by the interpretation of the spectral properties of remote sensing image. However, there are still relatively few studies using ML to predict fuel type for forest and land fires, thus providing the potential for more substantial research. Some studies in this field have been conducted[30-32].

Forest and Land Fire Detection

Detecting natural fires as soon as possible at the start of their occurrence and while they are still relatively small is essential to facilitate a fast and effective response. Traditionally, fires were detected by human observation, by distinguishing smoke from fire towers, or video on towers, airplanes, or in the field. All of such methodologies can be limited by spatial or temporal coverage, human error, the presence of smoke from other fires, and by the length of sunlight. Automatic detection of heat or smoke in infra-red or optical images can increase the spatial and temporal coverage of detection, increase detection efficiency in smoky conditions, and eliminate bias associated with human observation. Analytical tasks using the ML method for classification problems are fairly good. CNN (i.e., Deep Learning), which can extract features and patterns from spatial images and is widely used in object detection tasks, has recently been applied to the fire detection problem. Some of these applications are trained on terrestrial image-based models of fire and/or smoke. Several studies can be found in this field[33-35].

Perimeter and Severity Mapping of Forest and Land Fire

There are two management applications of fire maps: 1) Maps with good accuracy of perimeter locations of active fire are essential for daily planning of suppression and/or evacuation activities; including regrowth modeling 2,) Maps of the fire perimeter and fire severity are essential for assessing and estimating the economic and ecological impacts of forest fires and for recovery planning. In history, the perimeter of fire was mapped by a sketch from the air, from GPS on the ground or in the air, or by interpretation of aerial photographs. The development of methods for mapping fire perimeter and fire severity from remote sensing images has been an active research area since the advent of remote sensing in the 1970s. It is primarily concerned with the classification of active fire areas from inactive or unburned areas, burned areas from unburned areas, or a fire severity index such as the Normalized Burn Ratio[36].

Fire Behaviour Prediction

Generally, fire behavior includes physical processes and characteristics at various scales, including the rate of combustion, flaming, smoldering time, flame height, and depth of flame. Several studies dealing with this issue consist of fire spread rate, a burned area, fire growth, and fire severity prediction. Predicting the spread of wildfires is an important task for fire management agencies, particularly to assist in deploying suppression resources or anticipating evacuations in advance. Therefore, a large number of different approaches have been developed for modeling. There are quite a lot of studies in this regard[37-40].

TECHNOLOGY OUTLOOK OF FOREST, LAND FIRE AND PEAT SMOULDERING DRR IN BPPT AND IMPLEMENTATION OPPORTUNITY OF MACHINE LEARNING

This session will discuss the recommendation book of National Technology Congress (Kongres Teknologi Nasional/KTN) and or the outlook book of Disaster Risk Reduction Technology of Forest and Land Fire[41], particularly about the opportunity of ML implementation in the scenario framework for the application of forest and land fire DRR technology. The discussion results will be used as input to formulate a conceptual design of "Impact-Based Learning on Forest, Land Fire, and Peat Smouldering" DRR, which is the recommendation of this paper and to answer the aforementioned questions.

Technology Outlook of Forest and Peatland Fire DRR in BPPT

BPPT's Technology Outlook recommends 5 technologies for disaster risk reduction of forest and peatland fires, as shown in Table 2.

Table 2.
Priority Technology Terminology for Forest and Peatland Fire DRR

No	Priority Technology	Types of Technology
1.	Zero Burning Technology for land clearing	Charcoal and wood vinegar, compost, microbes
2.	Spatial Information Technology for *Fire Weather* and Hot Spot	FWI, SiPongi, Hotspot, Fire Spot, Burned Scar, InaFDRS, SIDIAN, WiNSS
3.	Real time Monitoring Technology for water level and water content in peatland	SIPALAGA, SMOKIES
4	Water Management Technology	*Canal Blocking*, hydrant pump
5.	Weather Modification Technology	Rain harvesting, smoke dispersing

The scenario for implementing the 5 priority technologies is recommended with the Industry 4.0 conceptual framework and the cycle of forest and peatland fires. Such a cycle is closely related to water availability in the annual water cycle, from the rainy season (abundant water) to the dry season (lack of water or water crisis), as presented in Table 3 and Figure 6.

Machine Learning Implementation Opportunity

As a complement to the 5 priority technologies' implementation scenarios, the BPPT's Forest and Land Fire Technology Outlook also recommend its implementation to be adjusted to the stages or cycle of disaster management. Thus, ML methods in science and management of forest and land fire provide big opportunities for applying various ML approach at every stage and disaster management cycle as illustrated in Figure 7, particularly in the pre-disaster and emergency response. ML method can be applied in (1) data mining and monitoring, (2) rewetting critical conditions, and (3) fire and haze suppression.

Challenge: Impact-based Forecasting and Machine Learning

3 challenges must be answered to fully apply ML, solve end to end problems, and achieve strategies from early detection until providing recommendations for the application of appropriate prevention and suppression technology as recommended in the BPPT Technology Outlook, both Big Data and methods as well as an algorithm which has the following characteristics:

1) Multi scale: global ←→ regional ←→ local ←→ parcel ←→ parameter;
2) (2) Multi-temporal: seasonal ←→ annual ←→ monthly ←→ daily ←→ hourly ←→ (near) real-time;
3) Impact-based forecasting: risk of fire prediction spatially, temporally, and the combination completed with mitigation recommendation.

The first two challenges can be met by choosing a combination of methods and applications. As described in the previous section, the third challenge can be met using the Impact-based forecasting paradigm.

How Impact-Based Forecasting Works

According to experts, Impact-based Forecasting will make weather predictions more relevant to citizens. The new approach will help determine what to do with specific weather conditions, not just a description of the weather, so citizens can take actions to save lives in unfavorable weather conditions.

Impact-Based Forecasting differs from the prediction method, which is usually delivered by meteorologists in a particular area. For example, the weather forecast will usually say: 50 mm of rainfall will fall on Thursday in the western part of Jakarta Special Capital Region. Using impact-based forecasting, the sentence will be: 50 mm of rainfall falls on the West of Jakarta Special Capital Region on Thursday and will cause several floodwaters in the Pesanggrahan riverbank, and will disrupt traffic passing in the area. This new approach will help save lives, improve decision-making, and lead to better planning among end-users because forecast warnings based on these impacts will be issued five days in advance. This means that stakeholders such as disaster managers, health care providers, and emergency rescue teams in weather sectors will receive forecasts and warnings with the appropriate impact through the most accessible media to them, thus enabling proper planning.

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Table 3.
The scenario of Priority Technology Implementation

		Business as Usual Condition	Outlook Scenario
Pre-Crisis Phase	Abundant water	o Canal Blocking technology in the industrial area has not been integrated with the surrounding area. o Stakeholders work according to their respective needs.	o Canal blocking technology and water management for industrial estates and community agricultural lands have been integrated. They use an optimum water management model to avoid the dangers of flooding and water shortages in water crisis times. o The establishment of a stakeholder communication forum related to big data Integration, modeling, data mining, AI, machine learning, IoT, and other Industry 4.0 needs o Stakeholders carry out routine coordination to evaluate the potential threat of open fire and smoldering peat fire and prepare plans to deal with them, including implementing zero burning technology for land clearing extensively.
	Enough water	▪ Stakeholders work according to their respective needs. ▪ Information on FDRS, FWI, hotspots, and similar information has not been followed up because it is still in the green or safe level.	▪ Information on FDRS, hotspots, and similar information is strengthened by models based on big data, AI, machine learning, and another similar system, strengthened by mapping and surveillance of areas prone to water shortages with an integrated UAV fleet. ▪ Stakeholders carry out routine coordination to anticipate the potential threats of an open fire and smoldering peat fire, including management of water distribution in canals, wetting dry peatlands with hydrant pumps, and modifying weather to fill canals.
Crisis Phase	Less water→ Water crisis	✓ In case the water starts to decrease, the stakeholders work according to their respective needs; there is no post yet. ✓ The monitoring of FDRS, hotspots, and similar information received various responses from each stakeholder.	✓ Monitoring with FDRS, hotspots, and similar information is strengthened by models based on big data, AI, machine learning, and another similar system and by mapping and surveillance of areas prone to water shortages with an integrated UAV fleet. ✓ Water management technology, wetting peatlands with hydrant pumps, modifying weather, improving drone fleets for surveillance deployment. ✓ Improved coordination and communication between stakeholders, especially at the national and regional levels ✓ Water bombing and haze depletion fleets are prepared and run immediately when a surface fire begins, and new smoldering occurs.

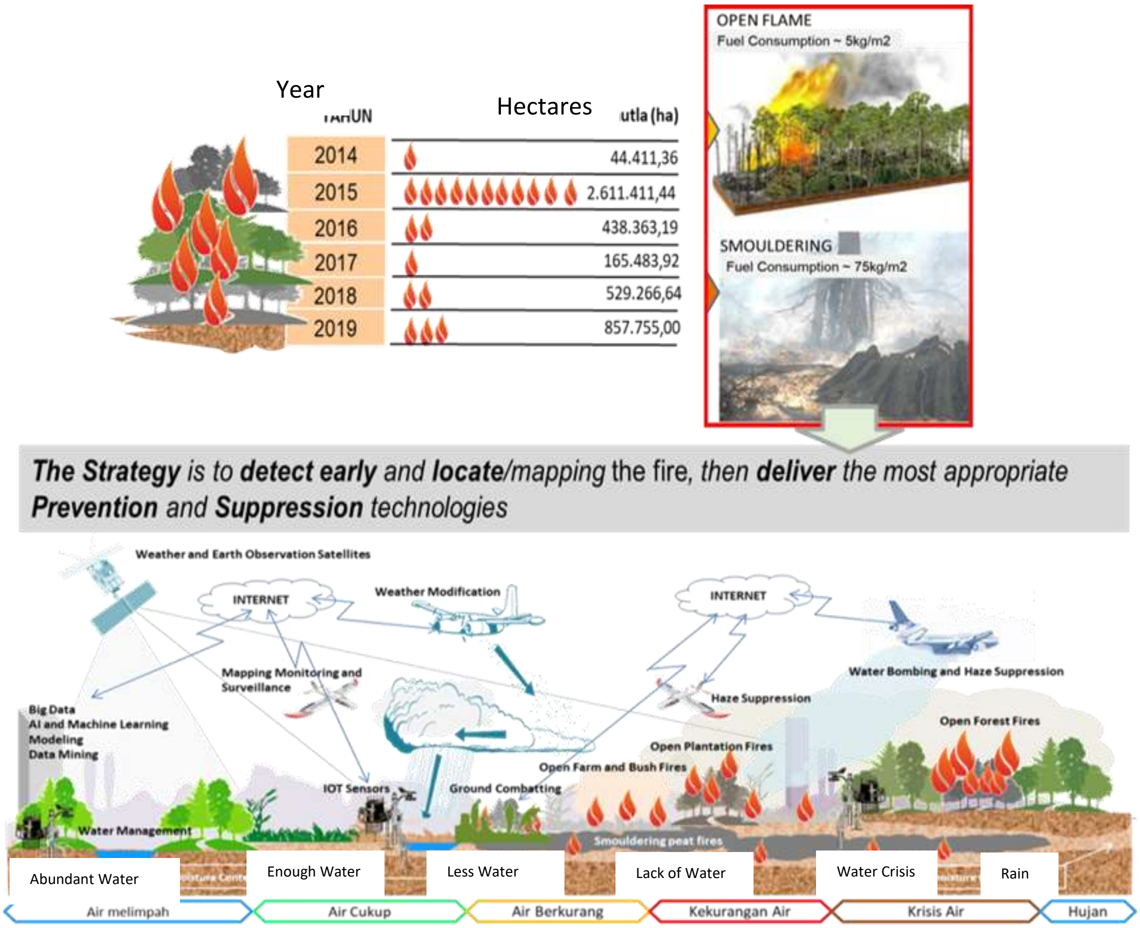

Figure 6.
A scenario of Priority Technology Implementation

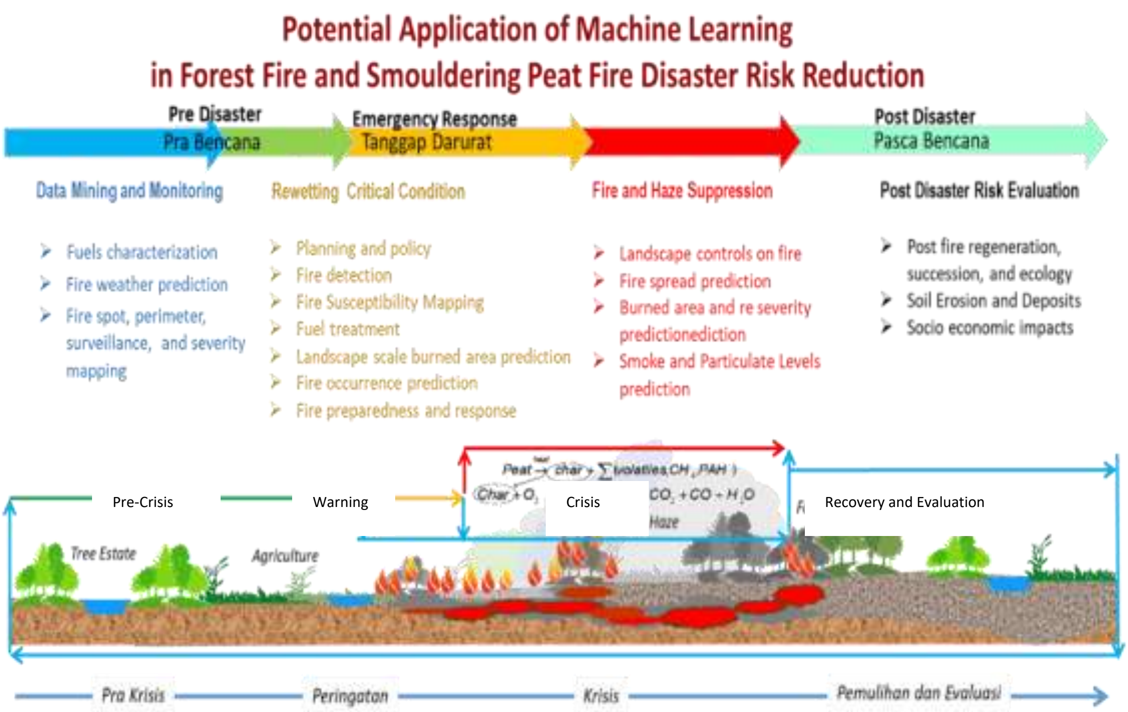

Figure 7.
The opportunity of Machine Learning Application for Forest Fire and Peat Smouldering DRR at Each Stage of Disaster Management Cycle

Recommendation: impact-based Learning of DRR for Forest Fire and Peat Smouldering

One of the recommendations provided to various policymakers can be described in a conceptual design diagram, as shown in Figure 8. Through widely available data such as big data at macro, meso, and micro scales, and applying machine learning and/or deep learning methods in producing an analysis of risk level for forest fire and peat smoldering.

The analysis result is a product of a certain event's learning process using appropriate parameters based on historical data, and thus, provide information on risk level in the affected area. Information with this approach might help produce recommendations and better planning for policymakers to reduce disaster risk of forest, land fire, and peat smoldering.

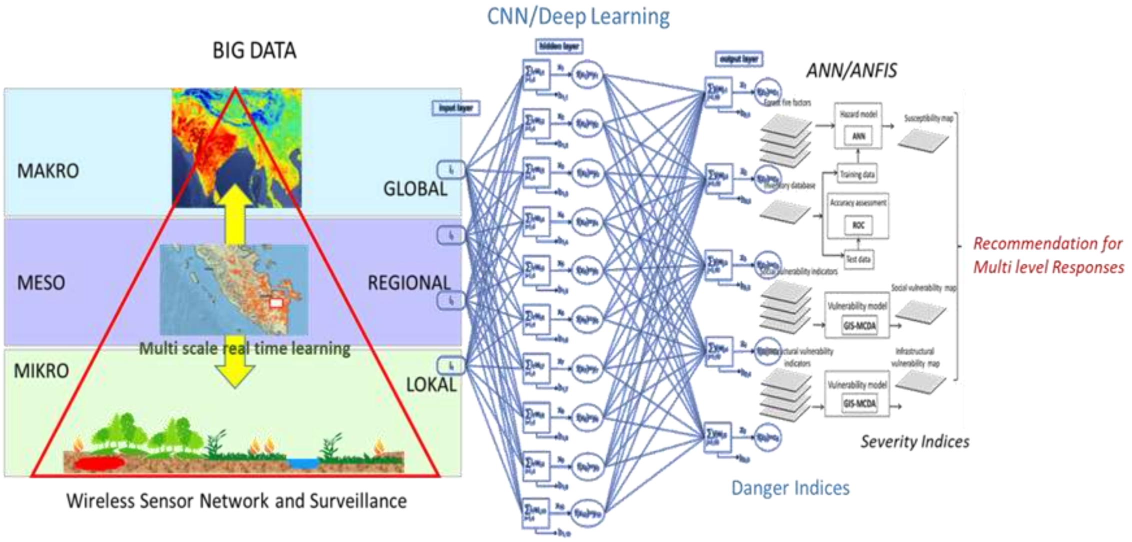

Figure 8.
Recommendation: Conceptual Design of Impact-Based Learning of Forest Fire and Peat Smouldering DRR

CONCLUSION

Once fires occur in a peat ecosystem, there are two biomass fires, i.e., open flame and smoldering peat fire. Smoldering peat fire consumes peat biomass, which is much larger than an open flame. Smoldering peat fires may burn for a long period and are well known for causing a big fire disaster in the world. In response to disaster risk reduction and climate change mitigation, there is a lot of research in the field of wildfire science and management. Currently, the use of machine learning has been widely developed, for instance, in the research of fire occurrence, susceptibility, and risk; fire behavior prediction; fire effects; fire weather and climate change; and fire management.

In line with the outlook on DRR technology of forest and land fires by BPPT, there are big opportunities to implement machine learning. Particularly, implementation at every stage of disaster management cycle of forest fire and peat smoldering. Opportunities can be found at the stage of (1) data mining and monitoring, (2) rewetting critical conditions, and (3) fire and haze suppression.

Through this article, a recommendation on the impact-based learning of disaster risk reduction for forest fire and peat smoldering is provided by using the machine learning method. It is expected to support better planning for stakeholders at different levels.

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