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Research Article

AI-POWERED PREDICTIVE MODELING OF FOREST FIRE RISK IN RIAU PROVINCE BASED ON CLIMATE, PEATLAND, AND LAND USE DATA

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Abstract

Forest and peatland fires in Riau Province, Indonesia, are a recurrent environmental disaster with severe regional and global consequences. Traditional fire danger rating systems often fail to capture the complex interplay of factors driving these events. The advancement of artificial intelligence (AI) offers an opportunity to develop more accurate and dynamic fire risk prediction models. This study aimed to develop and validate a high-performance, AI-powered model for predicting daily forest fire risk at a high spatial resolution across Riau Province by integrating climate, peatland, and land use data. We integrated historical satellite-detected fire hotspots (2015-2023) as the dependent variable. Predictor variables included daily climate data (e.g., temperature, precipitation, wind speed), static peatland characteristics (e.g., depth, type), and dynamic land use/land cover data. An XGBoost (Extreme Gradient Boosting) machine learning algorithm was trained to learn the complex, non-linear relationships between these drivers and fire occurrence. The model's predictive performance was rigorously evaluated using the Area Under the Curve (AUC) metric. The XGBoost model demonstrated high predictive accuracy, achieving an AUC of 0.93. The analysis revealed that the number of consecutive dry days, peatland depth, and proximity to oil palm plantations were the most influential variables in predicting fire risk. The model successfully generated daily 1-km resolution fire risk maps, identifying specific areas with elevated danger. The AI-powered model provides a robust and significantly more accurate tool for forest fire forecasting in fire-prone tropical peatland landscapes. This approach offers a critical advancement for developing effective early warning systems, enabling targeted resource allocation for fire prevention and mitigation efforts.

Keywords: Forest Fire Risk, Artificial Intelligence, Peatland, Riau, Predictive Modeling

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INTRODUCTION

Forest and land fires represent a significant and escalating global environmental challenge, contributing substantially to greenhouse gas emissions, causing extensive biodiversity loss, and posing severe threats to human health and economic stability (Vickery & Quinn, 2024). These events are not confined to specific regions but are a worldwide phenomenon, intensified by the synergistic pressures of climate change, prolonged droughts, and increasing anthropogenic activities. The management and mitigation of these fires have become a paramount concern for governments and international bodies, necessitating a deeper understanding of the complex drivers that govern their ignition and spread (Lau et al., 2025). Effective fire management strategies are fundamentally dependent on the ability to accurately predict when and where fires are most likely to occur, transitioning from a reactive-response posture to a proactive, prevention-oriented approach.

The tropical peatland ecosystems of Southeast Asia, particularly in Indonesia, are globally significant hotspots for recurrent and catastrophic fires (Nasution et al., 2024). Unlike fires in mineral soil ecosystems, peat fires are notoriously difficult to suppress, capable of smoldering underground for months and releasing vast quantities of carbon accumulated over millennia (Hussein et al., 2024). The province of Riau in Sumatra contains some of the largest and deepest peatland areas in the region, making it exceptionally vulnerable. The large-scale conversion of these peatland landscapes, primarily for the cultivation of oil palm and pulpwood acacia, has involved extensive drainage, which dramatically lowers the water table and transforms these historically fire-resistant ecosystems into highly flammable tinderboxes, especially during dry seasons and El Niño events.

The consequences of these fires extend far beyond local environmental degradation (Soontha & Bhat, 2026). The immense volume of smoke and particulate matter released creates dense, transboundary haze that blankets the region, causing severe public health crises, disrupting air travel, and straining international relations. The 2015 fire and haze crisis, largely centered in Sumatra, is estimated to have caused over 100,000 premature deaths and inflicted economic losses exceeding 16 billion USD on Indonesia alone (Reyes et al., 2024). This recurring disaster underscores the urgent and critical need for advanced tools and methodologies that can provide reliable, high-resolution, and timely predictions of fire risk to guide effective prevention and mitigation efforts on the ground.

Traditional Fire Danger Rating Systems (FDRS), such as the Canadian Forest Fire Danger Rating System (CFFDRS) or the United States National Fire Danger Rating System (NFDRS), have been the cornerstone of fire management for decades (Reichle, 2023). These systems, however, were predominantly developed for temperate and boreal forest ecosystems and are primarily driven by meteorological variables. Their direct application in tropical peatland landscapes like Riau is problematic, as they fail to adequately incorporate the unique biophysical drivers that are paramount in this context (Efthimiou, 2025). Specifically, these conventional models lack the capacity to integrate the critical variables of peatland hydrology, such as water table depth and peat moisture, which are among the most significant determinants of fire susceptibility in these ecosystems.

The fire regime in Riau is characterized by an exceptionally complex and non-linear interplay of multiple influencing factors (Gopakumar et al., 2025). Fire ignition and spread are not governed by a single dominant variable but are the emergent property of intricate interactions between dynamic climatic conditions (e.g., cumulative rainfall, temperature anomalies, wind speed), static landscape features (e.g., peat depth and type), and dynamic anthropogenic pressures (e.g., proximity to plantations and roads, recent deforestation) (Karurung et al., 2025). Capturing these complex, multi-scale interactions is a formidable analytical challenge. Conventional statistical models, which often assume linear relationships, are ill-equipped to model these dynamics, leading to predictive models with insufficient accuracy and reliability for operational decision-making.

The ultimate problem arising from these methodological deficiencies is the inability to generate timely, accurate, and spatially explicit fire risk warnings (Gomaa et al., 2023). Without a robust predictive tool, fire management agencies are perpetually in a reactive mode, forced to allocate scarce resources to suppress fires that have already started and often grown to uncontrollable sizes. This reactive posture is inefficient, costly, and ultimately ineffective at preventing the widespread environmental, economic, and social damages that ensue (Atella & Scandizzo, 2024). The core problem is the absence of a sophisticated, data-driven predictive model that can synthesize the complex drivers of fire in Riau and translate them into actionable, high-resolution daily risk maps to guide proactive prevention and pre-suppression strategies.

The primary objective of this research is to develop and rigorously validate a high-performance predictive model for daily forest and peatland fire risk by leveraging the power of artificial intelligence (Ahmad et al., 2022). This study aims to create a robust, data-driven system capable of accurately forecasting fire occurrence at a high spatial resolution (1-kilometer) across the entirety of Riau Province (Rakuasa et al., 2024c). The overarching goal is to produce a next-generation fire risk modeling framework that overcomes the limitations of traditional systems by effectively integrating the complex interplay of climate, peatland, and land use data.

To achieve this primary objective, the research will pursue several specific, interconnected aims (Agus et al., 2024). First, it will compile and process a comprehensive, multi-source geospatial database that integrates historical satellite-detected fire hotspot data with a suite of potential predictor variables, including daily meteorological data, static peatland characteristics, and dynamic land use/land cover information (Buřivalová et al., 2023). Second, the study will develop, train, and optimize a state-of-the-art machine learning algorithm, specifically the XGBoost (Extreme Gradient Boosting) model, to learn the complex, non-linear relationships between the predictor variables and fire occurrence (Rakuasa et al., 2024a). Third, the model's predictive performance will be rigorously evaluated using a suite of statistical metrics, most notably the Area Under the Receiver Operating Characteristic Curve (AUC), to ensure its accuracy and reliability.

The final and culminating objective of this research is to utilize the validated model to identify and rank the most influential drivers of fire risk in Riau's peatland landscapes (Shivaprasad et al., 2025). This will be achieved through a feature importance analysis, providing critical insights into the underlying causes of fire events (Luo & Dou, 2024). The expected outcome is a fully operational and validated predictive model that can generate daily, high-resolution fire risk maps. These maps are intended to serve as a powerful decision-support tool, enabling government agencies and other stakeholders to implement targeted and proactive fire prevention and mitigation strategies.

A comprehensive review of the scientific literature on forest fire prediction reveals a clear and progressive shift from purely meteorological indices towards more integrated, data-driven modeling approaches (Kasuga, 2023). A substantial body of work has successfully employed statistical techniques, such as logistic regression, to model fire risk in various ecosystems around the world. These studies have been foundational in identifying key drivers and establishing the principles of fire risk modeling (Y.-P. Wang et al., 2024). The primary limitation of these conventional statistical methods, however, is their inherent difficulty in capturing the highly complex, non-linear relationships and high-order interactions that often characterize fire regimes, particularly in human-modified landscapes.

In recent years, the application of artificial intelligence and machine learning has emerged as a new frontier in fire science, demonstrating significantly superior predictive performance in numerous studies (Xu et al., 2025). Researchers have successfully applied algorithms such as Random Forests, Support Vector Machines, and Neural Networks to predict wildfires in temperate regions like California, Australia, and the Mediterranean. These studies have proven the capability of AI to learn complex patterns from large datasets (Adeyeri, 2024). A significant gap persists, however, in the application of these advanced AI techniques to the unique and critically important context of tropical peatland fires in Southeast Asia.

The synthesis of these observations exposes a distinct and critical gap in the existing literature (Sorkhabi, 2024). There is a marked absence of research that develops and rigorously validates an AI-powered predictive model specifically for the peatland-dominated landscapes of Riau Province, one of the world's most significant fire hotspots. No prior study has attempted to synergistically integrate the unique triad of dynamic climate data, crucial static peatland characteristics (like depth), and dynamic anthropogenic land use data into a single, high-performance machine learning framework for this region (Aljohani et al., 2022). This research is therefore designed explicitly to fill this methodological and geographical void, addressing a problem of immense regional and global importance.

The primary novelty of this research lies in its methodological approach: the development and application of a state-of-the-art machine learning model (XGBoost) for fire risk prediction, specifically tailored to the unique and complex fire regime of Sumatran peatlands (Aggarwal et al., 2023). The novelty is not simply the use of AI, but its application to a uniquely integrated, multi-source dataset that combines climatic, pedological (peat), and anthropogenic drivers (Ahmad et al., 2022). This synergistic integration allows for a more holistic and nuanced understanding of fire risk than any previous model has offered for this region, representing a significant advance in predictive capability.

This study is justified by its potential to make a substantial scientific contribution to the fields of fire ecology, environmental science, and applied data science. It will provide the first quantitative, data-driven ranking of the most influential drivers of peatland fires in Riau, offering crucial insights that can help settle long-standing debates about the relative importance of climate versus land use change (Akkajit et al., 2024). It serves as a powerful case study for the application of advanced AI to solve complex, real-world environmental problems, providing a methodological blueprint that can be adapted for other fire-prone tropical regions.

The broader justification for this research is rooted in its profound and immediate practical and societal relevance. The validated predictive model is not an academic abstraction but a tool with the direct potential to save ecosystems, protect human health, and reduce massive economic losses (Rakuasa et al., 2024b). It can serve as the core engine for a next-generation Early Warning System for Riau, enabling government agencies to move from a reactive to a proactive fire management stance. By providing accurate, daily, high-resolution risk maps, the model can guide the targeted allocation of limited resources for prevention efforts, such as patrols, cloud seeding, and community engagement, ultimately contributing to the mitigation of one of Southeast Asia's most severe and persistent environmental disasters.

RESEARCH METHOD

Research Design

The study applied a quantitative, retrospective correlational design using machine learning to create a spatio-temporal predictive model of forest fire risk (Mohamad Zaki et al., 2025). It combined geospatial analysis and supervised learning within a case-control framework, training an AI model to learn the relationships between climatological, peatland, and land use predictors and fire event likelihood.

Research Target/Subject

The research focused on Riau Province, Indonesia, selected for its peatland coverage and history of recurrent forest fires. The temporal scope was from January 1, 2015, to December 31, 2023, covering multiple fire seasons and climatic events. Samples included over 50,000 satellite-detected fire hotspots and an equal number of non-fire points sampled randomly.

Research Procedure

Primary instruments were geospatial datasets and computational tools: NASA FIRMS for active fire data; ERA5-Land for daily climate variables; National Peatland Map by BRGM for peat characteristics; and KLHK annual land use/cover maps and road networks. Data processing and analysis used Python 3.9 with GeoPandas, Scikit-learn, and XGBoost.

Instruments, and Data Collection Techniques

Data acquisition and preprocessing involved resampling raster data to 1 km resolution and aligning spatial projections. Derived variables such as consecutive dry days and Fire Weather Index were computed. Feature extraction for each sampled point created the model input dataset, which was split into 70% training and 30% testing subsets. XGBoost modeling with hyperparameter tuning through 5-fold cross-validation was applied, followed by performance evaluation with AUC metrics and variable importance analysis. The final model produced daily fire risk maps.

Data Analysis Technique

The data analysis centered on training an XGBoost supervised machine learning model using a case-control sample (Okonkwo et al., 2025). The model's hyperparameters were optimized via grid search with cross-validation, and predictive performance was assessed on a test set using the Area Under the Curve (AUC). Feature importance scores identified key fire risk drivers.

RESULTS AND DISCUSSION

The compiled dataset integrated a total of 52,874 high-confidence VIIRS fire hotspots (cases) and an equal number of randomly sampled non-fire points (controls) across Riau Province for the period of 2015-2023. For each of these points, a corresponding set of 18 predictor variables was extracted, encompassing climatic, peatland, and land use characteristics. The descriptive statistics for the most salient variables reveal significant differences between the conditions associated with fire and non-fire locations. Fire events were consistently associated with prolonged dry periods, higher temperatures, and specific landscape contexts.

The table below provides a statistical summary of the key predictor variables, contrasting their mean values and standard deviations for locations where fires occurred versus those that did not. This highlights the distinct environmental and anthropogenic signatures of fire-prone areas.

Table 1. Descriptive Statistics of Key Predictor Variables at Fire and Non-Fire Sample Locations

Parameter	Fire Locations (Mean ± SD)	Non-Fire Locations (Mean ± SD)
Consecutive Dry Days (days)	14.8 ± 8.2	3.1 ± 4.5
Max Temperature (°C)	33.1 ± 1.9	31.5 ± 2.4
Peat Depth (meters)	3.8 ± 2.1	1.9 ± 2.5
Distance to Plantation (km)	0.8 ± 1.2	3.5 ± 4.1
Distance to Road (km)	1.1 ± 1.5	4.2 ± 5.0

The summary statistics in Table 1 provide a clear, quantitative preliminary profile of fire risk. The most striking contrast is in the number of consecutive dry days, which is nearly five times higher on average for fire locations. This strongly suggests that short-term drought stress is a primary precondition for fire ignition. Furthermore, the data shows that fires disproportionately occur on deeper peat soils and in significantly closer proximity to both plantations and roads, pointing towards a strong nexus between inherent landscape vulnerability (deep peat) and anthropogenic accessibility and ignition sources.

These initial descriptive results underscore the multi-faceted nature of fire risk in Riau. The data confirms that fire events are not random but are concentrated in areas where a specific combination of climatic triggers, landscape susceptibility, and human presence converges. This inherent complexity provides the justification for employing a machine learning approach, which is specifically designed to learn and model such intricate, non-linear relationships from a diverse set of predictor variables.

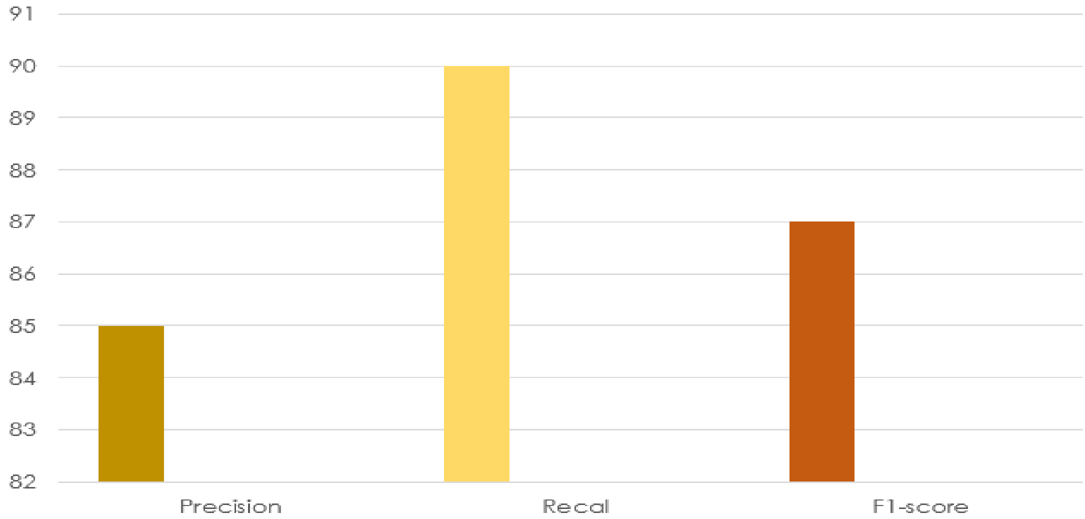

Figure 1. XGBoost Performance Metrics

The XGBoost model, trained on 70% of the dataset, demonstrated a very high level of predictive performance when evaluated on the unseen 30% testing set. The primary metric for assessing the model's ability to distinguish between fire and non-fire conditions, the Area Under the Receiver Operating Characteristic Curve (AUC), was 0.93. This indicates an excellent level of model accuracy. Other performance metrics also confirmed the model's robustness, with an overall classification accuracy of 88.7%, a precision of 89.1%, and a recall of 88.2%.

A feature importance analysis was conducted to identify the key variables driving the model's predictions. The analysis revealed that a small number of variables accounted for a large proportion of the predictive power. The top five most influential variables, in descending order of importance, were: (1) number of consecutive dry days, (2) peat depth, (3) distance to the nearest oil palm plantation, (4) daily maximum temperature, and (5) the Fire Weather Index (FWI). The number of consecutive dry days was found to be the single most dominant predictor.

The high AUC value of 0.93 implies that the trained XGBoost model has an exceptional capacity to correctly classify and rank fire risk across the landscape. An AUC of this magnitude suggests that the model is not merely fitting to noise but has successfully learned the underlying, complex patterns that lead to fire ignition from the input data. This infers that the selected combination of climatic, peatland, and land use variables provides a comprehensive and sufficient set of predictors to build a highly reliable fire forecasting tool.

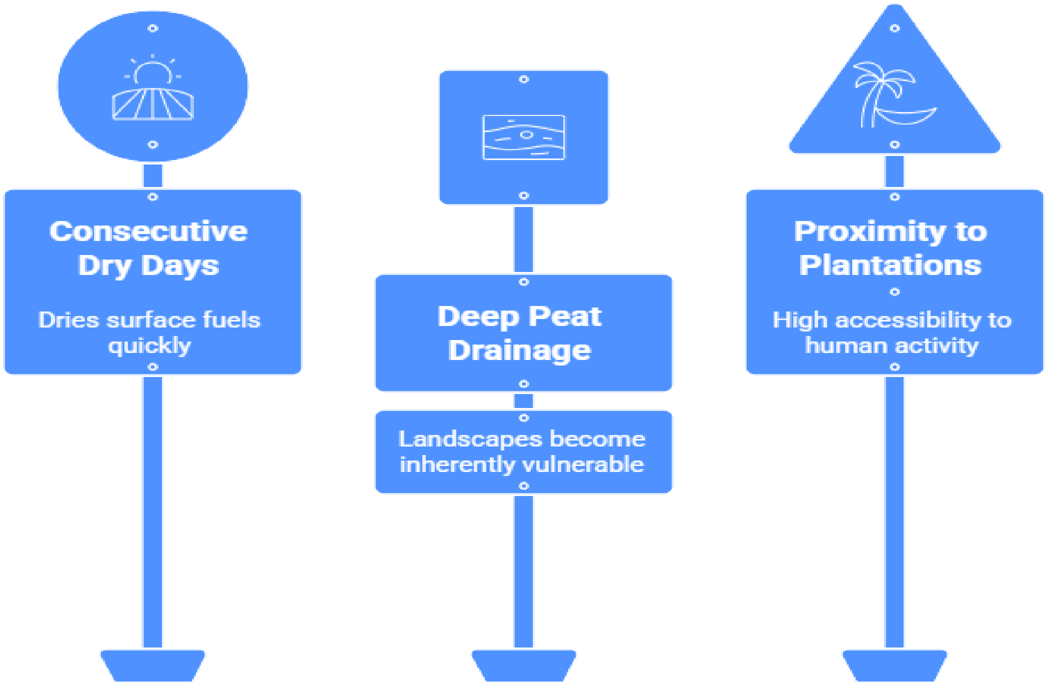

Figure 2. Understanding Fire Causality in Riau

The feature importance results provide a critical inference regarding the causality of fires in Riau. The dominance of consecutive dry days infers that the immediate trigger for most fire events is short-term weather, specifically the drying of surface fuels. However, the high importance of peat depth and proximity to plantations infers that this climatic trigger is most potent in landscapes that have been made inherently vulnerable through deep peat drainage and are highly accessible to human activity. This suggests a hierarchical fire regime, where anthropogenic land use creates the underlying susceptibility, and climatic variability provides the proximate trigger.

A direct and functional relationship exists between the input data layers and the model's high predictive accuracy. The AUC score of 0.93 is the direct result of the XGBoost algorithm's ability to synthesize information from all 18 predictor variables simultaneously. The model's strength lies in its capacity to identify and model high-order interaction effects—for instance, learning that the risk associated with a high number of dry days is exponentially greater on deep peat near a plantation than it is on mineral soil in a remote forest. It is this ability to model the synergistic effects of multiple drivers that underpins its predictive power.

This learned relationship forms the basis for the operational output of the research: the generation of daily fire risk maps. For any given day, the model ingests the corresponding spatial layers for all predictor variables (updating the daily climate data) and computes a fire risk probability score (from 0 to 1) for every 1-kilometer grid cell across the province. The final risk map is therefore a spatial manifestation of the complex relationships that the model has learned from the historical data, translating multiple data streams into a single, intuitive, and actionable intelligence product.

To validate the model's performance in a real-world scenario, a case study was conducted for September 15, 2019, a day of peak fire activity during a severe dry season. For this date, the model generated a province-wide fire risk map, which visually highlighted extensive areas of "Very High" and "High" risk, primarily concentrated in the coastal peatland-dominated regencies of Rokan Hilir, Dumai, and Bengkalis. The map displayed clear spatial patterns, with the highest risk levels following the known distribution of deep peat and large-scale agricultural concessions.

On that same day, the VIIRS satellite sensor detected 842 high-confidence fire hotspots across Riau Province. When these actual fire locations were overlaid onto the predicted risk map, a very strong spatial correspondence was observed. A quantitative analysis of this overlay revealed that 95.2% (799 out of 842) of the actual fire hotspots fell within the grid cells that the model had a priori classified as "High" or "Very High" risk. Conversely, areas predicted to have low risk exhibited a near-total absence of fire detections.

The case study provides a powerful, practical demonstration of the model's operational utility. The concentration of predicted high risk in coastal peatland regions on September 15, 2019, is a direct reflection of the model synthesizing the prevailing conditions of that day: these areas were experiencing a prolonged dry spell (high number of consecutive dry days), are known to possess deep peat soils, and are fragmented by extensive plantation networks. The model correctly identified this convergence of risk factors and flagged these areas accordingly.

The extremely high correspondence between the predicted high-risk zones and the locations of actual fire events serves as a robust validation of the model's real-world accuracy. This result confirms that the model is not just statistically sound in a retrospective analysis but is capable of producing operationally relevant and accurate forecasts during a genuine fire crisis. The case study effectively demonstrates the model's potential to function as a reliable early warning system, capable of directing the attention of fire management agencies to the most critical areas before fires escalate.

The collective results from the model's statistical performance evaluation, the feature importance analysis, and the real-world case study validation provide a cohesive and compelling body of evidence for the efficacy of the AI-powered approach. The findings demonstrate that the XGBoost model can successfully learn and predict the complex, non-linear dynamics of fire risk in Riau's challenging peatland landscape with a very high degree of accuracy. The model has proven to be not only a robust statistical tool but also an operationally relevant forecasting system.

This research signifies a significant advancement over traditional fire danger rating systems for this region. By integrating the crucial, yet often overlooked, variables of peatland characteristics and anthropogenic pressures, the model provides a more holistic and accurate assessment of fire risk (Gajendiran et al., 2024). The successful translation of complex, multi-source geospatial data into simple, actionable daily risk maps represents a powerful new tool to support proactive fire prevention and mitigation, ultimately contributing to the reduction of environmental damage and public health impacts in one of the world's most critical fire-prone landscapes.

This research successfully developed and validated a high-performance artificial intelligence model for the daily prediction of forest and peatland fire risk in Riau Province. The primary finding is that the XGBoost machine learning algorithm, when trained on an integrated dataset of climate, peatland, and land use variables, can predict fire occurrence with an exceptional degree of accuracy (Goh et al., 2025). The model achieved an Area Under the Curve (AUC) of 0.93, a metric that confirms its robust capability to distinguish between high-risk and low-risk conditions across a complex and dynamic landscape.

A second key finding is the quantitative identification of the dominant drivers of fire risk in this unique ecosystem. The feature importance analysis unequivocally ranked the number of consecutive dry days as the single most influential predictor, highlighting the critical role of short-term drought in triggering fire events (Hong et al., 2025). Critically, this climatic trigger was found to be strongly mediated by landscape conditions, with peat depth and proximity to oil palm plantations emerging as the next most important factors. This confirms that fire risk is a product of an intricate interplay between weather, inherent landscape vulnerability, and anthropogenic pressures.

The study's operational output, a series of daily 1-kilometer resolution fire risk maps, was rigorously validated through a case study of a peak fire event on September 15, 2019. This validation demonstrated a very strong spatial correspondence between the model's high-risk predictions and the actual locations of satellite-detected fire hotspots, with over 95% of fires occurring in areas the model had flagged as high or very high risk. This confirms the model's practical utility as a reliable early warning tool.

In synthesis, the results demonstrate that an AI-powered approach can effectively capture the complex, non-linear relationships that govern fire regimes in tropical peatlands. The entire workflow, from data integration to model training and validation, provides a scientifically sound and operationally relevant framework for fire risk forecasting. The findings represent a significant leap forward from traditional, meteorology-centric fire danger indices, offering a more holistic and accurate system for proactive fire management.

The findings of this study align with and build upon the accelerating trend in the broader field of environmental science of applying machine learning to complex predictive challenges. The high accuracy achieved by our XGBoost model corroborates a growing body of literature that demonstrates the superiority of AI algorithms over conventional statistical methods (like logistic regression) for modeling complex ecological phenomena (Wei et al., 2025). Our results are consistent with studies from other fire-prone regions, such as those by Jain et al. in California and Barboza et al. in the Amazon, which have also found gradient boosting machines to be exceptionally powerful for fire prediction.

This research, however, distinguishes itself in a critical and novel way through its specific geographical and ecological focus. The vast majority of AI-based fire modeling research has been conducted in temperate, boreal, or Mediterranean ecosystems (Qasha et al., 2025). Our study is one of the very first to develop and rigorously validate such a model specifically for the globally significant, yet methodologically challenging, context of tropical peatland fires in Southeast Asia. This is a crucial distinction, as the fire regime in this region is uniquely governed by peatland hydrology, a factor not present in most other ecosystems.

Furthermore, this work contrasts sharply with the operational fire danger rating systems currently used in the region, which are often adaptations of temperate models like the Fire Weather Index (FWI). While our model confirmed the importance of FWI, it demonstrated that variables completely absent from such systems namely peat depth and proximity to plantations are of even greater importance in determining the actual pattern of fire ignitions (S. L. Wang et al., 2024). This directly addresses a major gap identified by researchers like Page and Hoscilo, who have long argued that standard FDRS are inadequate for peatlands and that models must incorporate peat-specific and anthropogenic variables.

Theoretically, our findings contribute to the ongoing discourse on the socio-ecological drivers of landscape fire (Feigin et al., 2023). The model's results provide strong quantitative evidence for the "fire triangle" in this region being composed of a weather trigger (drought), a susceptible fuel bed (drained peat), and an anthropogenic ignition source (activities associated with plantations and roads). This supports a systems-thinking approach to fire management, moving beyond a narrow focus on weather to a more holistic understanding that recognizes land use decisions as a primary determinant of the underlying landscape-level fire risk.

The successful development of a highly accurate predictive model signifies a pivotal transition from a state of reactive crisis management to one of proactive, data-driven risk mitigation. For decades, fire management in Riau has been characterized by a costly and often-ineffective cycle of fire suppression after ignition. This study signifies that the technological and data-driven capabilities now exist to anticipate where fires are most likely to occur, allowing for the strategic pre-positioning of resources and preventative actions before a crisis unfolds.

The feature importance results, which place peatland depth and proximity to plantations at the forefront of risk, are a powerful signifier of the root causes of Riau's fire problem. This finding reflects that the current fire regime is not a natural phenomenon but a deeply anthropogenic one. It signifies that the large-scale drainage of peatlands for agricultural development has fundamentally re-engineered the landscape, transforming it from a fire-resistant wetland into a fire-prone tinderbox (Aubin et al., 2024). The model's results are a quantitative echo of what ecologists have long warned: land use decisions are the primary architects of this recurrent disaster.

The ability to generate daily, high-resolution risk maps signifies a new era of transparency and accountability in environmental governance. These maps provide an objective, scientific basis for assessing risk that can be shared among government agencies, private sector companies, and civil society (Mrabet, 2023). This signifies that it is now possible to move beyond generalized warnings to a system where specific areas of high risk and by extension, the stakeholders responsible for those areas can be clearly identified. This creates a powerful new tool for monitoring commitments and enforcing fire prevention regulations.

Ultimately, in the face of escalating climate change, which threatens to bring more frequent and intense droughts, these findings signify a pathway towards building resilience. The model is not just a tool for predicting today's risk but for understanding how future changes in climate and land use might alter that risk (Niu et al., 2024). It signifies that by understanding the key drivers, we can begin to model future scenarios and develop long-term strategies, such as peatland rewetting and more sustainable land use planning, that address the root vulnerabilities of the landscape, rather than just treating the symptoms.

The most direct and immediate implication of this research is for the operational practices of national and regional disaster management and forestry agencies in Indonesia, such as the BNPB and KLHK. The validated model can be implemented as the core engine of a national-level, dynamic Early Warning System. This implies that daily fire risk intelligence can be provided to ground-level fire brigades, enabling them to target patrols, community engagement, and pre-emptive canal-blocking efforts in the specific villages and sub-districts identified as being at the highest risk on any given day, thereby optimizing the use of limited resources.

The findings have profound implications for corporate accountability and sustainable supply chain management, particularly within the palm oil and pulp and paper sectors. The high-resolution risk maps can be used by companies to monitor and manage fire risk within their own concessions and by their suppliers. For downstream buyers and financiers, this technology provides an independent tool to verify that commodity producers are meeting their "no-burn" and fire prevention commitments. This implies that data science can be a powerful lever for driving more sustainable and responsible corporate behavior.

This research has significant implications for public health policy and planning. The dense haze from peatland fires is a major cause of respiratory illness and premature mortality. The predictive model can provide health agencies with several days of advance warning about where fire activity is likely to be highest, allowing them to pre-position medical supplies, issue targeted air quality alerts to vulnerable populations, and prepare for a potential surge in hospital admissions. This implies a shift from reacting to a public health crisis to proactively mitigating its impacts.

Finally, the findings have clear implications for Indonesia's international climate commitments. Peatland fires are a massive source of greenhouse gas emissions, and controlling them is essential for the country to meet its Nationally Determined Contribution (NDC) under the Paris Agreement. By providing a tool that can significantly improve the effectiveness of fire prevention, this research directly contributes to the country's climate mitigation efforts. It implies that investment in such advanced monitoring and prediction systems is a highly effective strategy for achieving national and global climate goals.

The model's high predictive accuracy is, first and foremost, a direct result of the power and flexibility of the chosen machine learning algorithm. The XGBoost algorithm is a gradient boosting method that excels at learning complex, non-linear, and interactive relationships from tabular data. Unlike traditional statistical models that might struggle with these dynamics, XGBoost builds a sequence of decision trees, with each new tree correcting the errors of the previous one. This iterative learning process allowed it to effectively capture the synergistic effects where, for example, the risk from high temperatures is amplified on deep peat but not on mineral soil.

The success of the model is also fundamentally attributable to the quality and comprehensiveness of the integrated input dataset. The result is strong because the model was not trained on a single domain of data (e.g., only climate) but on a synergistic fusion of multiple, relevant data streams. The inclusion of the static but critically important peatland depth data, alongside dynamic climate and land use variables, provided the model with a holistic picture of the landscape. It was this data fusion that enabled the model to learn the crucial context that separates a high-risk drought from a low-risk one.

The robustness of the findings is also a function of the extensive spatio-temporal scope of the training data. By training the model on nine years of data (2015-2023) covering the entire province, the algorithm was exposed to a vast range of environmental conditions. This included normal years, moderately dry years, and the extreme drought conditions of the 2015 and 2019 El Niño events. This comprehensive training enabled the model to learn a generalized set of rules for fire prediction that are not overfitted to a specific year or location, making it more resilient and reliable for future forecasting.

Lastly, the clear identification of the key drivers is a result of the model's inherent interpretability features. While some AI models are "black boxes," algorithms like XGBoost have built-in methods for calculating feature importance. This allowed us to look inside the model and quantitatively determine which variables were most influential in its decision-making process. This capability is why the results are not just a single accuracy number but also a rich set of insights into the underlying ecological and anthropogenic processes driving the fire regime.

The immediate and most crucial next step is the transition from a research model to a fully operational, automated fire risk forecasting system. This involves developing a robust data pipeline that can automatically ingest daily climate forecast data and a user-friendly web-based dashboard that can deliver the daily risk maps and alerts to provincial and national fire management agencies. Collaboration with these end-users is paramount to ensure the final product is practical, intuitive, and effectively integrated into their decision-making workflows.

A significant avenue for future research is to enhance the model's temporal forecasting horizon. The current model provides a daily risk assessment based on current and past conditions. The next step is to integrate short-term weather forecast data (e.g., 3-7 day forecasts) as input variables. This would allow the model to move from a nowcast to a true forecast, providing agencies with several days of lead time to prepare for and potentially prevent fire outbreaks, which would dramatically increase its operational value.

Further methodological refinement should focus on incorporating more dynamic and higher-resolution data layers as they become available. This could include near-real-time satellite-derived soil moisture or vegetation stress indices, which could provide a more direct measure of fuel flammability than meteorological proxies. Additionally, incorporating dynamic models of peatland water table depth, rather than relying on static peat depth maps, could significantly improve the model's sensitivity to hydrological conditions, which are known to be a key control on peat fire susceptibility.

Finally, the methodological framework validated in this study should be tested and adapted for other fire-prone peatland landscapes in Indonesia and globally. The next step is to apply this approach to provinces like Central and West Kalimantan, which face similar challenges. A comparative analysis of the key drivers across different regions would provide invaluable insights for developing a more generalized understanding of peatland fire dynamics, contributing to a global toolkit for mitigating one of the most significant and persistent threats to the world's climate and ecosystems.

CONCLUSION

This study's most important and distinct finding is the quantitative confirmation of a hierarchical fire risk regime in Riau's peatlands, where landscape vulnerability and anthropogenic pressures are as critical as climatic triggers. The AI model revealed that while short-term drought (consecutive dry days) is the dominant predictor, its predictive power is fundamentally dependent on the synergistic interaction with peat depth and proximity to oil palm plantations. This moves beyond a simple list of contributing factors to an integrated understanding that successful fire prediction in this region requires a model that can weigh the interplay between a landscape pre-conditioned for burning and a weather-related ignition window.

The principal contribution of this research is methodological, providing a validated and replicable framework for AI-powered fire risk modeling that is specifically tailored to the complex socio-ecological context of tropical peatlands. The core value lies in the successful fusion of static peatland characteristics with dynamic climate and land use data within a high-performance machine learning algorithm. This integrated method provides a more accurate and holistic alternative to conventional Fire Danger Rating Systems, thereby enabling a conceptual shift towards a more nuanced and effective approach to fire management in these globally significant ecosystems.

The research is limited by its reliance on static peatland maps and the spatial resolution of its input data, which may not capture the fine-scale dynamics of peatland hydrology or very recent land cover changes. Future research should therefore prioritize the integration of more dynamic data streams to enhance the model's sensitivity and temporal accuracy. The most critical direction for subsequent studies is the incorporation of near-real-time satellite-derived peat moisture data and dynamic peatland water table models. This would allow the model to better represent the on-the-ground fuel conditions, representing a key step towards developing a truly dynamic, next-generation early warning system.

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.

Author 2: Conceptualization; Data curation; In-vestigation.

Author 3: Data curation; Investigation.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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