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Review Article

A Review of Key Factors Influencing Forest Fire and Wildfire Susceptibility: The Role of Climatic, Environmental, Topographic, and Anthropogenic Variables

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ABSTRACT

Forest fires represent a significant environmental and socio-economic challenge, driven by the complex interplay of climatic, topographic, and anthropogenic factors. Many studies have utilised a wide range of fire-influencing variables, such as temperature, precipitation, wind speed, elevation, and others, to model fire susceptibility maps and develop predictive models. However, these studies often assume that readers are already familiar with the underlying mechanisms that link these factors to fire occurrence, without providing detailed explanations of how each variable contributes to ignition probability and fire spread. This paper aims to address this gap by offering an accessible and comprehensive synthesis of key variables influencing forest fire susceptibility. Based on findings from previous systematic reviews and recent literature, 22 critical fire factors are categorised into three groups: climatic and environmental factors, topographic variables, and anthropogenic influences. For each factor, intuitive explanations of its relationship with fire occurrence are provided to guide hypothesis-driven feature selection for fire mapping and modelling. Crucially, this review emphasises that while these factors are globally prevalent, their application requires statistical validation to account for regional differences in fire regimes. By clarifying the mechanisms behind fire-influencing factors, this review supports more robust fire risk assessments and informs evidence-based strategies for wildfire prevention and management.

Keywords: Anthropogenic influences, climatic variables, fire modelling, fire susceptibility mapping, remote sensing, topographic variables, wildfire prediction, wildfire risk factors

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INTRODUCTION

Understanding forest fires is crucial for analysing the relationships between various factors and fire occurrences. With the rapid advancements in artificial intelligence and the availability of extensive global remote sensing data, numerous studies have leveraged these developments to analyse forest fire incidents, whether to understand their occurrence or to assess the extent and damage caused by these events. Despite the abundance of research, our investigation into fire incidents in Malaysia (Chew et al., 2022a, 2025a; Chew, Ooi, Pang, & Hoi, 2024; Chew, Ooi, Pang, & Lim, 2024) has revealed a significant gap in the literature—there is a lack of in-depth reviews that delve into the intuition and insights behind individual factors and their correlation with forest fire occurrences.

The closest comparable work is a systematic review published by Chicas and Østergaard Nielsen (2022). While it is a comprehensive study that reviewed factors utilised by researchers worldwide in forest fire studies, it primarily focused on the frequency of the fire influencing factor usage across various literature. Unfortunately, it did not explore the theoretical underpinnings or insights behind these factors. For example, why does a lower Normalised Difference Vegetation Index (NDVI) correlate with higher fire occurrences? Such insights are invaluable for early-career researchers and scientists to connect the dots between factors and their influence on fire events. This gap motivates our study, which seeks to bridge this disparity by providing a deeper understanding of each factor's role in influencing forest fire occurrences.

In this paper, we examine highly influential factors that are widely acknowledged to correlate with forest fire incidents. We aim to discuss how each factor generally impacts fire occurrences and provide intuitive explanations for their effects. Previous studies have predominantly highlighted key factors based on their regional importance or frequency of usage, often assuming that readers already possess expertise in the domain of forest fires. This has likely contributed to the lack of accessible discussions on the broader implications of these factors.

To address this, our study offers an accessible entry point for new researchers in the domain of forest fire studies. We aim to provide a comprehensive understanding of how these factors influence fire occurrences, focusing on 22 critical variables. It is important to highlight that the 22 factors to be reviewed in this study were selected as they are most frequently used in the global literature (Chicas & Østergaard Nielsen, 2022); however, this frequency of usage does not guarantee causal relevance in every local context. In fact, as noted by previous authors, the frequency of use is often related to data availability rather than physical necessity. Therefore, this review serves to provide an intuitive basis for these factors to guide feature selection. Consequently, further analysis and investigation should be conducted by researchers in their local context or specific study area to statistically validate these variables. Some of the techniques that can be considered include

Information Gain, Correlation Analysis, or Random Forest variable importance ranking. This is necessary to avoid circular reasoning, where factors are selected simply because they have been commonly adopted across the global literature. Additionally, researchers must also acknowledge the fundamental uncertainty and resolution limits associated with satellite-based remote sensing data, which serves as the primary source for these models. The subsequent discussion is organised into five sections: Section 2 summarises insights from previous systematic reviews, Section 3 covers climate and environmental factors, Section 4 focuses on topographic variables, Section 5 explores anthropogenic factors, and Section 6 provides the conclusion, highlighting key findings and future research directions.

INSIGHTS FROM PREVIOUS SYSTEMATIC REVIEWS OF FOREST FIRE FACTORS

Forest fires are complex events influenced by a multitude of factors. In the systematic review (Chicas & Østergaard Nielsen, 2022) an extensive exploration was undertaken to identify the most influential factors affecting forest fires. The exhaustive analysis examined a total of 144 factors from 94 publications spanning the years from 2001 to 2021. Among the factors that emerged as highly significant were slope, elevation, aspect, land cover, NDVI, temperature, precipitation, and wind speed. It is important to note that the sequence in which these factors are listed does not indicate their rankings. The frequency of factor usage among the 94 articles has been leveraged to establish their rankings. Notably, the prevalence of these factors was attributed to their wide global availability in existing databases, unlike more specific anthropogenic factors that require extraction from local databases.

While the review was comprehensive in reporting the frequency of use of each influencing factor across many studies, it implicitly assumed that readers are familiar with these factors and their correlations with fire ignition. To address this gap, this paper focuses on investigating the influence of the general key factors impacting forest fires, specifically categorising them into three groups: (i) climatic and environmental factors, (ii) topography, and (iii) anthropogenic factors. This categorisation is adopted from the literature to provide a structured framework, although we acknowledge that overlaps exist, particularly for variables like Land Cover, which operate across categories. Furthermore, 'climatic' and 'environmental' categories are combined in this paper as their distinction in fire modelling is often fluid. For instance, environmental variables such as soil moisture are predominantly driven by climatic conditions, making a strict separation impractical. Examining the role of these factors provides valuable insights into their relationship with fires, enriching the understanding of fire behaviour. Moreover, it aids in determining the factors that should be extracted, guiding the selection of relevant variables for constructing a fire susceptibility map or a fire model.

It is crucial to differentiate between fire susceptibility mapping and causal physical modelling, as the primary objectives of these modelling techniques are different. Susceptibility mapping relies on statistical correlations for predictive modelling using machine learning or statistical methods. On the other hand, causal physical modelling, which includes physical-based models and Computational Fluid Dynamics models typically adopt mathematical equations based on the fundamentals of fire behaviour, such as heat transfer or fluid dynamics, to simulate the occurrence or spread of fire. In contrast, this review focuses on the former, susceptibility mapping, by synthesising spatially explicit variables commonly utilised as the input for machine learning and statistical modelling. These intuitive explanations serve as a guide for feature engineering and data preprocessing, rather than a definitive description of physical fire dynamics in every biome.

The value of moving from purely data-driven approaches to those grounded in physical intuition is exemplified by our previous case studies. Our study focused on a specific fire incident that occurred in March 2023 in the Rompin district of Pahang, Malaysia, where the spatial extent of the burnt area was validated using the MCD64A1 dataset (Chew, Ooi, & Pang, 2023). This incident was analysed in relation to temperature and precipitation, leveraging the Google Earth Engine platform (Chew, Ooi, Pang & Lim, 2023). A ten-year temporal analysis of the location revealed that the highest temperatures and lowest precipitation levels consistently occur around March. This window aligns with the twenty-year FIRMS hotspot trends observed in the region (Chew et al., 2022b), showing that temperature increases and precipitation decreases as the primary fire month of March approaches. Such localised validation reinforces the necessity of understanding the underlying mechanisms of each factor to ensure robust feature selection for fire susceptibility models.

CLIMATE AND ENVIRONMENTAL FACTORS

Climatic and meteorological conditions significantly influence the likelihood of fire occurrence, as they directly affect moisture levels, fuel accumulation, rate of spread, and combustion dynamics (Syphard et al., 2008; Vilar et al., 2010). Factors such as precipitation, temperature, solar radiation, and wind speed play a pivotal role in the life cycles of flora and fauna, influencing fuel production, facilitating fuel drying for ignition, and affecting the spread of wildfires (Tavakkoli Piralilou et al., 2022). The key climate and environmental variables considered in this study, along with their definitions, optimal conditions for fire occurrence, and justifications, are summarised in Table 1.

While Table 1 provides an overview of individual climatic and environmental factors, a practical consideration for modellers is the issue of multicollinearity. Some of the variables listed in Table 1, including NDVI, NDMI, and soil moisture, are by nature highly correlated and physically related. Hence, multicollinearity analysis, such as the Variance Inflation Factor (VIF),

Table 1
Summary of fire influencing factors (Climate and environmental factors)

Factors	Short Definition	Optimal for Fire	Justification	References
Temperature	Degree of hotness	(+) Higher	Lower humidity Lower soil moisture Lower fuel moisture Drier condition Drier fuel (dead leaves/ branches) Drier vegetation Higher Drought Index Lower NDVI Amplifying evaporation and plant transpiration	(Ghorbanzadeh, Valizadeh Kamran, et al., 2019; Nur et al., 2023; Vardoulakis et al., 2020; Westerling et al., 2016)
Precipitation (Rainfall)	Rainfall	(-) Lower	Lower humidity Lower soil moisture Lower fuel moisture Drier condition Drier fuel (dead leaves/ branches). Drier vegetation Higher Drought Index Less heat energy to ignite fire	(Bravo et al., 2010; Eskandari et al., 2021; Nur et al., 2023)
Wind speed	Air movement	(+) Higher	Higher rate of fire spread	(Li et al., 2021; Syphard et al., 2008)
NDVI	Vegetation density	(-) Lower	Drier vegetation Reduced fuel moisture	(Bui et al., 2017, 2019)
Soil moisture	Water Content in Soil	(-) Lower	Lower soil moisture Drier vegetation Drier fuel (dead leaves/ branches) Less heat energy to ignite fire	(Bartsch et al., 2009; Chuvieco et al., 2004; Laguardia & Niemeyer, 2008; Sazib et al., 2022)

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Table 1 (*continued*)

Factors	Short Definition	Optimal for Fire	Justification	References
Palmer Severity Drought Index (PDSI)	Assessing drought conditions based on precipitation and temperature	(-) Lower	Lower PDSI Insufficient moisture in soil and atmosphere to meet the needs of the local ecosystem	(Palmer, 1965; Saim & Aly, 2022)
Solar radiance	Amount of radiant energy emitted by sun received by the earth's Surface	(+) Higher	More sunlight exposure Higher temperature Lower soil moisture Drier vegetation	(Babrauskas, 2014; Byram, 1943; Haigh, 2011; Kuznetsov & Baranovskiy, 2013; Sayad et al., 2019)
Topographic Wetness Index (TWI)	Water accumulation in relation to topography	(-) Lower	Less space for water accumulation Lower soil moisture Drier vegetation	(Adams et al., 2021; Harris & Taylor, 2015; Kane et al., 2015; Porensky et al., 2018; Pourtaghi et al., 2016; Sörensen et al., 2006)
Land Surface Temperature (LST)	Temperature of earth's surface	(+) Higher	Drier condition Drier vegetation Drier fuel	(Li et al., 2023; Maffei et al., 2018; Sekertekin & Bonafoni, 2020)
Normalised Difference Moisture Index (NDMI)	Water content in vegetation	(-) Lower	Lower water content in fuel (vegetation) Drier fuel Drier vegetation	(Gao, 1996; Jackson et al., 2004; Rabiei et al., 2022; Sakellariou et al., 2020)
Relative humidity	Moisture in air	(-) Lower	Less water is absorbed from atmosphere by vegetation Lower soil moisture	(Feistel & Lovell-Smith, 2017; Peng et al., 2006)
Land cover	Earth's landscape	Higher human activities land cover	Land surfaces with a higher potential for interaction with human elements have a greater likelihood of fire occurrence in the case of anthropogenic fires	(Bustillo Sánchez et al., 2021; Nur et al., 2022, 2023; Oliveira et al., 2012; Syphard et al., 2008; Tavakkoli Piralilou et al., 2022; Vilar et al., 2010)

can be exploited to perform the check. Furthermore, dimensionality reduction techniques such as Principal Component Analysis (PCA) can also be performed before introducing the variables into a predictive model to prevent redundancy.

Temperature

Elevated temperatures are undeniably linked to the occurrence of wildfires (Ghorbanzadeh, Valizadeh Kamran, et al., 2019), with prolonged dry seasons globally leading to unprecedented bushfire incidents (Vardoulakis et al., 2020). These temperature increases are frequently linked to drier conditions (Westerling et al., 2016), amplifying evaporation and plant transpiration, consequently reducing soil moisture levels (Pourtaghi et al., 2015). According to Nur et al. (2023), heightened temperatures significantly raise the probability of fire ignition or sustained burning by bringing the fuel closer to its ignition point, thereby accelerating the combustion process. These changes in climatic conditions significantly impact forest ecosystems, leading to vegetation dryness and increased vulnerability to forest fires. The combination of elevated temperatures and decreased soil moisture establishes an environment where forests are more susceptible to ignition and rapid fire spread.

Precipitation

Precipitation, also referred to as rainfall, significantly influences forest fire dynamics (Bravo et al., 2010). It plays a crucial role in determining moisture levels and the distribution of vegetation, thereby impacting both the moisture content of the fuel and the soil, ultimately affecting the rate at which fires spread (Eskandari et al., 2021; Nur et al., 2023).

Reduced rainfall leads to lower soil moisture content, making forests more susceptible to fire ignition and spread. With lower soil moisture levels, vegetation becomes drier and more susceptible to ignition. The accumulation of dry fuels, such as dead leaves and branches, creates an environment highly conducive to combustion. Additionally, reduced moisture in live fuels makes them more prone to ignition, requiring less heat to be ignited. Drought conditions, often resulting from low precipitation, further increase the risk of forest fires. The combination of dry fuels and decreased vegetation moisture fosters rapid fire spread and intensification.

Conversely, higher precipitation during the fire season can hinder fire occurrence by elevating fuel moisture levels, limiting ignition, and controlling fire spread (Bravo et al., 2010). However, Oliveira et al. (2012) suggested that precipitation occurring outside the fire season might influence fire incidents by stimulating seasonal vegetation growth. This growth could potentially increase the availability of fine fuels, particularly in grasslands, facilitating easier ignition and fire spread during the primary fire season (Oliveira et al., 2012).

Wind Speed

Wind speed significantly impacts the dynamics and spreads of wildfires (Li et al., 2021; Syphard et al., 2008). Strong winds play a significant role in rapidly spreading fires across the landscape and carrying the fire over long distances, igniting new spots several kilometres ahead of the primary fire front (Nur et al., 2023). Cruz and Alexander (2019) comprehensively analysed 118 wildfires in different ecosystems, including temperate shrublands, Australian dry eucalypt forests, and North American conifer forests. It was found that the forward rate of spread of fires in dry forest conditions is strongly influenced by wind speed. The study revealed that the forward rate of spread was approximately 10% of the wind speed. In other words, a higher wind speed corresponds to a higher rate of fire spread, leading to more rapid and extensive spread of fires.

Normalised Difference Vegetation Index (NDVI)

NDVI serves as an indicator of vegetation density and coverage near the Earth's surface, directly influencing the probability of forest fires (Bui et al., 2017, 2019). This index characterises the condition, health, and moisture content of vegetation (Nhongo et al., 2019). A decline in NDVI values indicates dry vegetation, signifying reduced water levels and elevating the potential for wildfires (Bui et al., 2017; Nur et al., 2023).

Soil Moisture

Soil moisture, identified as a crucial factor in plant physiological processes, serves as an indicator of drought conditions (Laguardia & Niemeyer, 2008). It significantly influences the moisture levels of live fuels, impacting the heat required for plant ignition (Bartsch et al., 2009). Furthermore, soil moisture directly governs fuel dryness, affecting dead fuels primarily found in the ground, thereby serving as an indicator of drought conditions (Chuvieco et al., 2004). This moisture content directly influences the dryness levels and water equilibrium of fuels, profoundly impacting the dead vegetation lying on the surface (Sazib et al., 2022).

Palmer Drought Severity Index (PDSI)

Drought Index, which is based on the Palmer Drought Severity Index (PDSI), is widely used to gauge agricultural drought by considering precipitation and temperature effects on soil moisture availability. It utilises a temperature-driven evapotranspiration algorithm to deplete moisture levels (Saim & Aly, 2022). This index's data provides assessments for landscape drought and surface water balance.

The PDSI, developed by Palmer (1965) uses a mathematical model to evaluate drought severity. It combines precipitation, temperature, and locally available water capacity to quantify moisture supply and demand over time. Detailed descriptions of this model can be found in Palmer's original manuscript (Palmer, 1965). Lower PDSI values signify insufficient soil and atmospheric moisture to meet ecosystem needs, highlighting drought conditions.

Solar Radiance

Solar radiance, also known as solar radiation, refers to the total amount of radiant energy emitted by the Sun and received by the Earth. The energy necessary for life and driving various environmental processes, such as photosynthesis, evaporation, and climate patterns (Haigh, 2011). The amount of solar radiation received on Earth's surface varies significantly depending on seasonal cycles, slope orientation, and terrain gradient (Byram, 1943). For instance, north- and south-facing slopes receive differing amounts of solar radiation due to the Sun’s changing position throughout the year, while steep and gentle slopes influence the intensity and distribution of sunlight received.

Elevated levels of solar radiation are closely associated with increased temperatures and decreased soil moisture, as higher radiation enhances evaporation rates, thereby exacerbating water deficits in the soil (Sayad et al., 2019). Furthermore, prolonged exposure to high solar radiation can heighten the risk of wildfires by drying vegetation and soils, creating conditions conducive to ignition and spread. In certain cases, concentrated solar rays may act as an ignition source for forest fires, further emphasising the link between solar radiation and wildfire risk (Babrauskas, 2014; Kuznetsov & Baranovskiy, 2013).

Land Surface Temperature (LST)

LST refers to the temperature of the Earth's surface as measured by remote sensing instruments, typically on satellites. It serves as an indicator of the energy and water exchange between the land surface and atmosphere, influencing the rate and timing of plant growth (Li et al., 2023). Additionally, LST affects surface energy balance, regional climates, heat fluxes, and energy exchanges (Sekertekin & Bonafoni, 2020).

LST is a crucial parameter in various environmental and climatic studies, including those related to forest fires, as it provides insight into the heat emitted from the ground, which can influence vegetation dryness and fire risk. High air temperatures and prolonged periods without rainfall may increase the LST captured by remote sensing devices (Maffei et al., 2018). Generally, higher LST signifies drier conditions that make vegetation more prone to ignition. Studies indicate that higher LST anomalies usually result in longer forest fire durations and larger affected areas (Maffei et al., 2018).

Normalised Difference Moisture Index (NDMI)

NDMI was devised by Gao (1996) to estimate the water content of vegetation. It is also used to assess water stress levels in vegetation, where water stress refers to the condition in which vegetation experiences insufficient moisture for growth. NDMI is also instrumental in agriculture for crop yield estimation and drought assessment (Jackson et al., 2004), and it also plays a crucial role in monitoring changes in plant health. NDMI provides critical insights for forest fire risk assessment by indicating moisture levels within vegetation. In forest fire susceptibility mapping, higher NDMI values correlate with lower forest fire risk due to higher detected moisture content (Sakellariou et al., 2020). Studies have also shown a high correlation between fire points and NDMI (Rabiei et al., 2022).

Relative Humidity

Relative humidity is a measure of the amount of moisture in the air compared to the maximum amount the air can hold at a given temperature (Feistel & Lovell-Smith, 2017). It plays a significant role in forest fire risk assessment, as higher relative humidity levels help keep vegetation moist by allowing them to absorb moisture from the atmosphere, thereby reducing fire risk. Conversely, lower relative humidity levels can lead to the drying of vegetation and increased fire susceptibility (Peng et al., 2006).

Land Cover

Land cover, also known as land use, represents the surface features of the Earth's landscape and has been linked to the incidence of fires (Nur et al., 2022; Syphard et al., 2008; Vilar et al., 2010). It depicts the arrangement, structure, and intrinsic characteristics of the landscape (Nur et al., 2023). Varied characteristics inherent in different land use types, such as their load and moisture content, can significantly impact the initiation and spread of fires (Bustillo Sánchez et al., 2021). In cases of anthropogenic fires, land cover signifies the vegetation within a particular area, portraying different fuel types that reflect their potential interaction with human elements (Oliveira et al., 2012). Different land cover patterns exert distinct influences on wildfire distribution and risk, a relationship closely associated with the interplay between the type of cover and human activity is also suggested by (Tavakkoli Piralilou et al., 2022).

Furthermore, in the context of remote sensing-based susceptibility mapping, land cover classes often serve as the primary proxy for fuel continuity. While fuel continuity is a critical determinant of fire spread, it is rarely treated as a standalone spatial variable due to the difficulty of directly measuring continuous fuel loads via satellite imagery.

TOPOGRAPHY

Topographic characteristics exert influence over vegetation distribution, composition, and flammability, and they play a significant role in local climate variations (Prasad et al., 2006). The structure of the forest canopy and the composition of species within it are notably affected by the variations in topography across the landscape (Kalantar et al., 2020). Variables such as elevation, slope, and aspect were acquired from the DEM to characterise topographic attributes. The primary topographic variables examined in this study, including their definitions, optimal conditions for fire occurrence, and supporting justifications, are summarised in Table 2.

Elevation (Altitude)

Elevation, also commonly known as altitude, signifies the vertical distance above a specific reference point, typically sea level, and generally represents the height of the land's surface above this reference point. Elevation serves as a critical factor influencing the spread and severity of wildfires, exhibiting associations with local climatic variations, vegetation distribution, composition, and flammability (Ghorbanzadeh, Valizadeh Kamran, et al., 2019). Additionally, it stands as a pivotal factor linked to temperature, moisture, and wind dynamics, profoundly impacting vegetation structure, fuel moisture, and air humidity (Oliveira et al., 2014). Regional climate differences are notably influenced by elevation, establishing it as a crucial feature (Tavakkoli Piralilou et al., 2022).

Research by Pu et al. (2007) found that most burned areas in North America occur at lower elevations (below 500 m). Similarly, Mohammadi et al. (2014) observed that fires are more frequent at lower elevations with gentle slopes and short distances from farmland, areas where human activity is concentrated. These findings suggest that human activities near farmland, typically situated at lower elevations, contribute to higher fire occurrence. While tourism activities such as camping (Suhardono et al., 2024) are present at both lower and higher elevations, human activity is typically more concentrated at lower elevations. This higher density of human presence at lower elevations has been speculated to contribute to elevated fire risk

Higher moisture levels found in elevated terrains act as a preventive measure against severe wildfires (Ghorbanzadeh, Blaschke, et al., 2019). Observations have indicated that fire behaviour trends are less distinct at higher altitudes due to increased precipitation levels (Ljubomir et al., 2019). However, Hong et al. (2019) speculate the possibility of widespread fire occurrence is heightened at higher altitudes due to the impact of wind action.

Overall, the literature presents mixed findings on whether higher or lower elevations are more prone to wildfire occurrence, as this relationship depends on regional factors and interacting environmental conditions. These contradictions likely stem from regional

Table 2
Summary of fire influencing factors (Topography)

Factors	Short Definition	Optimal for Fire	Justification	References
Elevation (Altitude)	Vertical distance above sea level Note: Affects climate, vegetation distribution, and composition.	(-) Lower	Higher temperature Higher accessibility More human activities	(Mohammadi et al., 2014; Pu et al., 2007; Suhardono et al., 2024)
		(+) Higher	Higher wind speed Higher spread rate	(Hong et al., 2019)
		(+) Higher	*Alternative Opinion (Lower Risk)* Higher precipitation Lower Temperature Lower fire risk	(Ghorbanzadeh, Blaschke, et al., 2019; Ljubomir et al., 2019)
Slope	Degree of steepness	(-) Lower	Higher accessibility More human activities	(Conedera et al., 2011; Widayati et al., 2010)
		(+) Higher	Higher windspeed Higher rate of spread	(Nur et al., 2022; Pourtaghi et al., 2015)
Aspect	Direction of slope	Southern	More sunlight energy Higher temperature Higher wind speed Lower soil moisture Lower humidity	(Adab et al., 2013; Prasad et al., 2008; Salavati et al., 2022; Sayad et al., 2019)
Hillshade	Intensity of sunlight depends on the terrain	(+) Higher	More sunlight exposure Higher temperature Drier vegetation	(Adaktylou et al., 2020; Iverson & Prasad, 2003; Razali et al., 2010)
Topographic Wetness Index (TWI)	Water accumulation in relation to topography	(-) Lower	Less space for water accumulation Lower soil moisture Drier vegetation	(Adams et al., 2021; Harris & Taylor, 2015; Kane et al., 2015; Porensky et al., 2018; Pourtaghi et al., 2016; Sörensen et al., 2006)

climatic variations. For example, in some regions, higher elevations are associated with increased precipitation and cooler temperatures which reduce fire risk, whereas in others, they may experience stronger winds and drier vegetation that increase susceptibility. Hence, the influence of elevation must be interpreted within the specific climatic context of the study area

Slope

Slope refers to the degree of incline or steepness of the land surface, and is generally expressed as a percentage or angle. It acts as an indicator of the rate of elevation change (Ljubomir et al., 2019) and controls both biodiversity and vegetation distribution (Tavakkoli Piralilou et al., 2022). Slope angles play a crucial role in fire behaviours.

Slope inclination greatly influences fire ignitions by restricting accessibility; typically, higher degrees of slope tend to limit accessibility (Oliveira et al., 2014). In a case study conducted in Switzerland (Conedera et al., 2011), findings revealed a higher frequency of anthropogenic fires occurring on gentler slopes, specifically those below 33^{o}, indicating a greater incidence of fire events. Furthermore, Widayati et al. (2010) also emphasised the restricted accessibility, indicating that a slope threshold of 20^{o} becomes a limiting factor for forest harvesting.

Slope influences both the speed and direction of fire spread (Kamran et al., 2014), often showing a high correlation with the formation and progression of forest fires (Bui et al., 2017). The rate of fire movement is faster on upward slopes. An increase in slope degree correlates with a faster rate and intensification of fire spread (Nur et al., 2022, 2023). Steep terrains significantly influence local wind formation, accelerating fire speed (Adab et al., 2013). Bustillo Sánchez et al. (2021) also accentuated that steeper areas facilitate rapid fire expansion, whereas less steep areas impede fire distribution.

Aspect

Aspect refers to the direction the slope is facing (Ljubomir et al., 2019), influencing the amount of solar radiation (i.e., sunshine) received through sunlight exposure (Salavati et al., 2022; Tavakkoli Piralilou et al., 2022). It describes the maximum rate of change in elevation between cells and their adjacent neighbours (Ljubomir et al., 2019; Prasad et al., 2008). This factor influences an area's climate in terms of exposure to temperature, winds, humidity, and fuel moisture.

Southern areas often experience more forest fires due to several environmental factors as vegetation tends to be drier and less dense on south-facing slopes compared to north-facing ones (Adab et al., 2013). South-facing aspects receive more direct heat from sunlight, resulting in higher temperatures, stronger winds, lower humidity, and decreased fuel moisture levels, leading to drier and less dense vegetation compared to north-facing slopes (Adab et al., 2013; Prasad et al., 2008; Salavati et al., 2022). These conditions contribute significantly to an increased potential for fire occurrences. Typically, the risk of forest fires is higher on south-facing slopes as they tend to be warmer and drier than north-facing slopes (Sayad et al., 2019).

Conversely, north-facing slopes receive less sunlight compared to their southern counterparts, retaining more moisture and supporting healthier vegetation (Kamran et al., 2014). On the other hand, Kamran et al. (2014) highlighted that east-facing slopes receive direct sunlight earlier in the day compared to west-facing slopes.

On the other hand, north-facing slopes receive less sunlight than their south-facing counterparts (Kamran et al., 2014). Consequently, north-facing slopes tend to retain more moisture, supporting healthier vegetation. These studies (Ghorbanzadeh, Blaschke, et al., 2019; Kalantar et al., 2020; Pourtaghi et al., 2015) suggested that fire spreads faster on east-facing slopes due to increased solar radiation in mountainous areas.

Hillshade

Hillshade represents the intensity of sunlight on a terrain surface, highlighting variations in illumination caused by topographic features. Hence, it can be used to assess the solar radiation difference due to differences in angle, aspect, and position (Iverson & Prasad, 2003). It is commonly used in geographic analysis to visualise the effects of sunlight and shadow on the landscape. Fires tend to spread more rapidly on slopes and are affected by the aspect of the slope relative to the sun. This aligns with earlier discussions that south-facing slopes have a higher risk of forest fires (Adab et al., 2013; Sayad et al., 2019).

Hillshade values are derived from the angle of the terrain relative to the position of the light source. Hence, they do not correspond to any physical units like degrees or meters. Instead, they are a relative measure of light and shadow intensity, typically ranging from 0 to 255, where 0 indicates complete shadow (no illumination) and 255 indicates full illumination (maximum sunlight).

While no direct studies have been identified in the literature linking hillshade values to fire occurrence, Adaktylou et al. (Adaktylou et al., 2020) demonstrates that greater sunlight exposure increases surface temperature (Razali et al., 2010), leading to warmer and drier conditions and accelerating vegetation drying, which contributes to higher fire risk and intensity.

Topographic Wetness Index (TWI)

TWI (Beven & Kirkby, 1979), a quantitative metric designed to assess water availability in relation to topography and has been widely used in hydrological studies to understand how landscape features influence moisture distribution. The TWI evaluates soil moisture by integrating water inflow from upslope catchment areas and downslope drainage for individual cells (Porensky et al., 2018). Commonly, TWI is utilised to quantify hydrological processes and topographic control (Sörensen et al., 2006).

TWI measures the landscape's tendency to accumulate water, with higher values indicating wetter areas and lower values indicating drier areas. As a result, places with higher TWI will have higher soil moisture, which can further reduce the probability of a fire occurrence. These regions typically exhibit a positive annual water balance, where water supply exceeds water loss through evapotranspiration, resulting in higher soil moisture levels (Adams et al., 2021).

Conversely, lower TWI values are associated with drier conditions, frequently observed in elevated locations such as ridge tops and plateaus. Studies (Adams et al., 2021) conducted in Mountain Ash forests have demonstrated a correlation between low TWI values and high wildfire intensity, indicating that reduced water availability significantly influences fire behavior. Consequently, TWI can be used to identify areas at least risk of fire during fire incidents characterised by high intensity and rapid spread. Additionally, TWI also serves as an important predictive indicator for fire incidents and risk assessment (Harris & Taylor, 2015; Kane et al., 2015; Pourtaghi et al., 2016).

ANTHROPOGENIC FACTORS

Anthropogenic refers to things caused or influenced by human activities in the environment. While the preceding factors focus on environmental influences affecting forest fire occurrences, various studies (Zhang et al., 2023) suggest that human activities might hold greater significant than natural phenomena in initiating wildfires. Spatial patterns of wildfire ignition exhibited a strong correlation with human access to natural landscapes, highlighting the proximity to urban (i.e., settlement) areas and roads as one of the most influential contributing factors. Moreover, the construction of roads or railways and fire sources generated from mobile vehicles will aggravate the risk of forest fires (Bui et al., 2019). The main anthropogenic variables influencing forest fire susceptibility, together with their definitions, optimal conditions for fire occurrence, and justifications, are summarised in Table 3.

Distance to Roads

Distance to roads is a crucial metric in understanding the accessibility to forest areas prone to fire ignition. Numerous studies (Martínez et al., 2009; Vilar et al., 2010) have identified the proximity to roads as a significant factor influencing forest fires, reflecting the extent of anthropogenic activity and human interactions within these landscapes. For instance, it can be assumed that a shorter distance to roads from the forest indicates easier accessibility and potentially more human activities.

Table 3
Summary of fire influencing factors (Anthropogenic factors)

Factors	Short Definition	Optimal for Fire	Justification	References
Distance to roads	-	(-) Shorter	Higher accessibility More human activities	(Martínez et al., 2009; Vilar et al., 2010)
Distance to urban area (settlement)	-	(-) Shorter	Higher accessibility More human activities	(Nur et al., 2023; Sachdeva et al., 2018; Tavakkoli Piralilou et al., 2022)
Distance to stream / river	Water resources	(-) Shorter	More human activities	(Pourtaghi et al., 2016)
		(+) Further	Further water sources Lower soil moisture Drier vegetation	(Nur et al., 2023)
Socio-economic variables	Unemployment rate	(+) Higher	High social tension Increase vandalism	(Martínez et al., 2009; Sebastián-López et al., 2008)
Nighttime light	Artificial light generated by human activities from remote sensing images	(+) Higher	More human activities	(Zhang et al., 2023)
Population density	Human Impact Index (HII)	(+) Higher	More human activities	(Oliveira et al., 2012; Sanderson et al., 2022)

However, a significant limitation of this variable, and anthropogenic factors in general, is the inability to distinguish between intentional ignitions and accidental fires. Distance to roads only indicates human accessibility, effectively aggregating both potential arsonists and accidental ignition sources into a single spatial metric, which limits the ability to model specific ignition behaviours.

Distance to Urban Area (Settlement)

Similar to the proximity to roads, the distance to settlements is a pivotal metric that gauges accessibility to forested regions and significantly influences the ignition of wildfire incidents (Sachdeva et al., 2018; Tavakkoli Piralilou et al., 2022). Factors such as the distance to recreational areas and roads, alongside human settlements, serve as indicators of accessibility to forested zones susceptible to wildfires, often attributed to human activities (Nur et al., 2023). Supporting this, Pham et al. (2020) identified distance from roads and settlements as the predominant variables influencing fire incidents in Pu Mat National Park, Vietnam.

Distance to Stream/ River

Distance to streams significantly impacts forest health by providing essential water resources (Ghorbanzadeh, Valizadeh Kamran, et al., 2019; Sachdeva et al., 2018). It is also closely tied to forest conditions, as rivers often serve as crucial water sources (Nur et al., 2023). These rivers frequently attract human recreational activities, and the associated human presence significantly contributes to wildfire incidents (Pourtaghi et al., 2016). Pourtaghi et al. (2016) found that distance to rivers, particularly in the range of 300-450 m, showed the highest correlation with fire occurrence. However, it can also be argued that shorter distances to streams or rivers may facilitate firefighting efforts by improving access to water sources. Although several studies have incorporated distance to rivers as a variable in fire susceptibility mapping and machine learning models, detailed investigations into its direct correlation with fire occurrence remain relatively limited.

Socio-economic Variables

The unemployment rate has been identified in studies within the European Mediterranean setting as a potential contributing factor to the fire occurrence (Martínez et al., 2009; Sebastián-López et al., 2008). However, the underlying reasons for this correlation remain ambiguous. This relationship is often interpreted either as a broad indicator of social tension, potentially leading to increased instances of vandalism in rural areas.

Nighttime Light

Nighttime light intensity data effectively capture various human activities, as highlighted by the authors' results in (Zhang et al., 2023). The authors utilised nighttime light data as a substitute for Gross Domestic Product (GDP) to fulfil the resolution requirement in their study. GDP, typically characterised by coarse spatial resolution, is replaced by nighttime light, which comprises remote sensing images with high spatiotemporal resolutions, relying on artificial light generated by human activities. Consequently, the authors postulated that this light intensity data more accurately and directly captures variations in human activities compared to GDP. In essence, their study highlighted nighttime light alongside population density, road density, and railway density as key socioeconomic indicators to outline human activities.

Population Density

Population density represents the distribution of potential causative agents, considering factors such as human activities and interactions that can contribute to forest fire ignition and spread (Oliveira et al., 2012). Higher population density often correlates with increased human activity. This increased activity can lead to a greater risk of fire incidents due to factors such as campfires, debris burning, and machinery use. To quantify the human footprint or human influence, the Human Impact Index (HII) (Sanderson et al., 2022) can be exploited to measure the extent of human impact on natural environments.

CONCLUSION AND FUTURE REMARKS

This study has reviewed and synthesised the key factors influencing forest fire susceptibility, highlighting the critical roles of climatic, environmental, topographic, and anthropogenic variables. Forest fire occurrences are shaped by the combined influence of these factors rather than by a single variable. Climatic conditions such as temperature, precipitation, wind speed, and solar radiation directly impact fuel moisture levels and fire behaviour. Topographic attributes, including slope, elevation, and aspect, affect local microclimates, vegetation patterns, and human accessibility, all of which contribute to variations in fire risk. Anthropogenic factors, such as proximity to roads and settlements, population density, and socio-economic indicators, further influence fire susceptibility through human activities and land-use practices.

Importantly, this paper has sought to bridge the gap in the literature by providing intuitive explanations of how each factor contributes to fire occurrence, aiming to support early-career researchers and practitioners in understanding these complex relationships. By offering a detailed synthesis of 22 critical variables, this study provides a foundation for selecting appropriate factors in fire susceptibility mapping and model development.

Nevertheless, while this review provides a general overview of global trends, local adaptation is still essential. For instance, in tropical countries such as Malaysia, where fire regimes are predominantly anthropogenic (Chew et al., 2022a) and most of the serious fires occur in peat swamp areas (Miettinen et al., 2017). These areas may be influenced by specific factors such as peat soil moisture or monsoonal rainfall patterns that differ from the standard natural fire regimes often cited in the literature. Given that various locations experiencing forest fires may be affected by distinct factors (Pourtaghi et al., 2016), it is crucial to conduct investigations that are specific to the area of interest to identify the predominant influencing factors. Furthermore, it is essential to address the temporal mismatch often found between static raster layers and dynamic fire events. To mitigate this issue, particularly in regions with distinct seasonal variations (e.g., temperate zones), we recommend utilising seasonal aggregates rather than static annual averages. This approach ensures the accurate capture of phenological changes in vegetation and varying fire risk. Future research should also aim to distinguish more clearly between ignition drivers (predominantly anthropogenic) and spread drivers (climatic/topographic), and move beyond binary occurrence mapping to assessing fire intensity and severity, acknowledging that even in human-dominated regimes, climatic conditions may act as critical amplifiers of fire intensity and severity.

To improve the accuracy of fire susceptibility model, there is also a need to integrate dynamic and high-resolution data sources, incorporating both antecedent meteorological conditions (to capture lag effects) and near real-time environmental indicators, to improve the accuracy of fire susceptibility models. Early exploratory work on temporal sampling for fire classification (Chew et al., 2020) and recent performance comparisons of machine learning algorithms across Peninsular Malaysia (Chew et al., 2025b) underscore the potential for high-fidelity detection models in this region. The application of advanced artificial intelligence and machine learning techniques offers significant potential for capturing the complex and non-linear interactions among these variables. Furthermore, interdisciplinary collaboration that combines environmental science, remote sensing, and socio-economic analysis will be essential for developing effective fire management strategies.

Ultimately, by clarifying the physical and environmental mechanisms behind these variables, this review empowers researchers to transition from purely data-driven 'black-box' approaches to hypothesis-driven modelling. This ensures that feature selection is not merely an exercise in maximising statistical metrics, but is grounded in physical reality, leading to more robust and interpretable fire susceptibility models. For instance, in the context of machine learning, researchers utilising decision trees can apply this domain knowledge to better interpret the resulting decision rules, ensuring that the model outputs are logically sound and translate into effective prevention strategies.

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AUTHOR CONTRIBUTIONS

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CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

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