Generative AI for Predicting 2D and 3D Wildfire Spread: Beyond Physics-Based Models and Traditional Deep Learning

Haowen Xu[a], Sisi Zlatanova[a,*], Ruiyu Liang[b], Ismet Canbulat[b]

[a]GRID, School of Built Environment, UNSW Sydney, NSW 2052 Australia
[b]School of Minerals and Energy Resources Engineering, UNSW Sydney, NSW 2052 Australia

Abstract

Wildfires continue to inflict devastating human, environmental, and economic losses globally, as tragically exemplified by the 2025 Los Angeles wildfire and the urgent demand for more effective response strategies. While physics-based and deep learning models have advanced wildfire simulation, they face critical limitations in predicting and visualizing multimodal fire spread in real time, particularly in both 2D and 3D spatial domains using dynamically updated GIS data. These limitations hinder timely emergency response, infrastructure protection, and community safety. Generative AI has recently emerged as a transformative approach across research and industry. Models such as Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), Transformers, and diffusion-based architectures offer distinct advantages over traditional methods, including the integration of multimodal data, generation of diverse scenarios under uncertainty, and improved modeling of wildfire dynamics across spatial and temporal scales. This position paper advocates for the adoption of generative AI as a foundational framework for wildfire prediction. We explore how such models can enhance 2D fire spread forecasting and enable more realistic, scalable 3D simulations. Additionally, we employ a novel human-AI collaboration framework using large language models (LLMs) for automated knowledge extraction, literature synthesis, and bibliometric mapping. Looking ahead, we identify five key visions for integrating generative AI into wildfire management: multimodal approaches, AI foundation models, conversational AI systems, edge-computing-based scenario generation, and cognitive digital twins. We also address three major challenges accompanying these opportunities and propose potential solutions to support their implementation.

Keywords: Generative AI, Wildfire Propagation, Fire Spread Simulation, Large Language Models, Retrieval-Augmented Generation,

1. Introduction

Wildfires and bushfires have emerged as one of the most destructive natural disasters of the 21st century, leaving a devastating trail across natural ecosystems, agricultural lands, and densely populated urban regions (Bowman et al.,

*Corresponding author.
Email addresses: haowen.xu1@unsw.edu.au (Haowen Xu), s.zlatanova@unsw.edu.au (Sisi Zlatanova), ruiyu.liang@unsw.edu.au (Ruiyu Liang), i.canbulat@unsw.edu.au (Ismet Canbulat)

2020; Doerr and Santín, 2016). These fast-moving fires not only cause immense structural damage and loss of human life but also result in widespread economic disruption and long-term environmental degradation. The release of smoke, fine particulate matter, and toxic gases during large-scale bushfires contributes significantly to air pollution, impacting public health and exacerbating climate change in cities across the globe (Johnston et al., 2012; Urbanski, 2014). A stark example of this escalating crisis was the 2025 Los Angeles wildfire season, during which the Palisades and Eaton wildfires tore through Southern California. Together, they caused an estimated $250 billion in economic losses, destroyed thousands of homes, and displaced entire communities, inflicting deep physical and emotional suffering on affected populations (EPA, 2025; Gazette, 2025). These events underscore the urgent need for accurate and timely wildfire forecasting systems. In particular, real-time bushfire propagation simulation-capable of predicting fire spread pathways and identifying at-risk zones-plays a critical role in supporting firefighting operations, emergency evacuation planning, and long-term fire hazard mitigation strategies (Baptiste Filippi et al., 2009; Sullivan, 2009c; Wang and Zlatanova, 2019; Wang et al., 2014).

A variety of wildfire propagation models have been developed, each rooted in distinct computational approaches. Physics-based models (e.g., FARSITE, SPARK, Prometheus) simulate fire spread using physical laws of combustion, heat transfer, fuel conditions, and wind dynamics (Finney, 1998; Mell et al., 2007; Miller et al., 2015), offering detailed outputs but requiring extensive computation and environmental inputs—often limiting their use in real-time scenarios (Dipierro et al., 2024). Empirical models, like McArthur's Fire Danger Index, rely on historical fire behavior to produce rapid, region-specific predictions, but struggle with generalizability across diverse ecosystems (Noble et al., 1980). Traditional machine learning models (e.g., decision trees, support vector machines) have been used for fire ignition and risk classification (Jain et al., 2020), though their capacity to simulate dynamic fire progression is limited. In contrast, deep learning models have recently gained momentum for 2D fire spread forecasting, due to their ability to capture complex spatiotemporal relationships in fire behavior (Andrianarivony and Akhloufi, 2024; Shadrin et al., 2024). Architectures such as CNNs, RNNs, and U-Net variants have been applied to wildfire segmentation and short-term spread prediction, leveraging remote sensing, meteorological, and topographic data (Ghali and Akhloufi, 2023; Vargas, 2025). These deep learning models (e.g., CNNs and RNNs) often outperform traditional physics-based simulators in runtime, scalability, and—in data-rich environments—predictive accuracy, as they learn complex patterns and variability directly from empirical observations rather than relying on explicit physical formulations (Radke et al., 2019). However, deep learning-based fire models still face key limitations that prevent them from enabling more advanced fire prediction capabilities with higher spatial and temporal resolution in real time. Most models remain constrained to **2D spatial domains** (Andrianarivony and Akhloufi, 2024) and **lack integration and real-time augmentation of multimodal inputs**, such as meteorological, topographic, and vegetation (fuel) data (Radke et al., 2019; Abdollahi and Yebra, 2025), which often change dynamically as fire propagates across the landscape. In addition, many existing models **cannot simulate vertical fire dynamics**, limiting their effectiveness during fast-evolving wildfire events (Xu et al., 2024f).

Building on this direction, emerging generative AI models—such as Variational Autoencoders (VAEs), Generative Adversarial Networks (GANs), Transformers, and diffusion models—offer transformative advantages over earlier deep learning architectures like CNNs and RNNs, particularly in the context of complex environmental modeling tasks such as fire propagation. Unlike traditional models that are often constrained by localized spatial features, limited sequential memory, and sparse or missing data, generative AI models can learn expressive latent representations, capture complex spatiotemporal dependencies, and generate high-resolution outputs from sparse or heterogeneous inputs (Kingma et al., 2013; Goodfellow et al., 2014; Vaswani et al., 2017; Ho et al., 2020). For instance, Transformers enable global attention across long time-series and spatial domains, making them particularly effective in fusing multimodal datasets such as remote sensing imagery, topographic data, real-time meteorological feeds, and vegetation maps (Dosovitskiy et al., 2020; Tay et al., 2022). Diffusion models and GANs have demonstrated the ability to synthesize highly realistic spatial patterns, which can enhance the fidelity of fire spread predictions even under uncertain or rapidly changing conditions (Rombach et al., 2022; Saharia et al., 2022). These strengths position generative models as a promising foundation for real-time, high-resolution bushfire forecasting systems capable of adapting to dynamic environments with greater accuracy and robustness.

Motivated by this potential, the objective of this position paper is to investigate how the convergence of generative AI techniques and emerging multimodal datasets can enable the development of next-generation bushfire prediction systems. Specifically, we explore how these technologies can facilitate real-time data fusion, enable high-fidelity spatial modeling, and enhance forecasting accuracy—capabilities that are essential for improving situational awareness and operational decision-making during fire emergencies (Dilo and Zlatanova, 2011). By delivering timely and reliable predictions, such systems hold the potential to significantly strengthen firefighting coordination, evacuation planning, and strategic fire management. To support this investigation, we first conduct an overview review of existing deep learning approaches applied to fire propagation prediction, focusing on their strengths and limitations. Distinct from prior studies, we adopt a representation learning-driven methodology that leverages Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG) to automate knowledge extraction from over 150 research articles retrieved from academic databases such as IEEE Xplore and Scopus using specialized queries. We then examine recent advancements in generative AI—including VAEs, GANs, Transformers, and diffusion models—that have been used to simulate and forecast fire dynamics, highlighting their advantages over conventional deep learning methods. Finally, we extend this analysis by evaluating how these emerging models can be repurposed or adapted to enable enhanced predictive accuracy, support data augmentation, and facilitate multimodal fire dynamics simulation and real-time fire behavior modeling based on dynamic input data. Looking ahead, we outline five strategic directions to guide this integration: (1) the development of multimodal approaches, (2) the deployment of AI foundation models, (3) the implementation of conversational AI systems, (4) edge-computing-based generation of wildfire scenarios, and (5) the advancement of cognitive digital twins. Alongside these visions, we examine three key challenges that accompany this paradigm shift and propose potential solutions to address them.

2. Previous Reviews in Fire Spread Management

Several previous studies have conducted comprehensive literature reviews on predicting bushfire spread using simulation techniques, machine learning, and deep learning. This section begins by summarizing these reviews, highlighting how both simulation models and deep learning approaches have been applied to fire propagation prediction. The overview of previous review articles aims to provide a comprehensive understanding of the existing AI applications in wildfire spread prediction and to identify gaps where generative AI models can be leveraged to address challenges faced by traditional simulation and deep learning approaches.

2.1. Wildfire Simulation Models and Traditional Machine Learning

Wildfire simulation models are traditional, well-established tools that simulate and predict bushfire spread by solving physical and empirical equations based on fuel, weather, and terrain conditions—originating from foundational models like Rothermel's in the 1970s (Rothermel, 1972; Finney et al., 2012), and they have long served as the backbone of operational fire management and planning systems. Based on their underlying rationale, these models can be classified into several categories, as presented in Table 2.1, and are summarized through multiple previous studies (Sullivan, 2009b,d,a; Finney et al., 2012).

Table 1: Fire simulation models based on different underlying principles

Model Type	Core Principle	Examples	Strength
Physical Models	Based on first principles of physics and chemistry (e.g., combustion thermodynamics, heat transfer, fluid dynamics)	FIRETEC, WFDS, FIRESTAR, IUSTI, Grishin	High fidelity, models full fire–fuel–atmosphere interaction, scientific rigor
Quasi-Physical Models	Includes physical processes (e.g., energy conservation, heat transfer) but omits combustion chemistry, often uses simplified fire shape assumptions	UoS (Spain), LEMTA, FIRESTAR-lite	Balance between physical realism and computational feasibility

Empirical Models	Derived purely from statistical regression of observed fire behavior (no physical basis); field or lab-based	McArthur FDRS, CSIRO Grass Meter, CFBP (Canada)	Easy to use, computationally light, good for operational tools
Quasi-Empirical Models	Empirical models informed or supported by a physical framework (e.g., use physical insights to design empirical terms)	Rothermel model, BEHAVE, Noble-McArthur model	Widely used in practice, moderate complexity
Mathematical Analogue Models	Use abstract mathematical constructs (e.g., cellular automata, percolation theory, wavelet propagation) not rooted in real fire physics	Cellular Automata models, Huygens' wavelet, Prometheus, SiroFire	Flexible, suitable for exploratory simulation, fast prototyping

On the application level, a recent study conducts a comprehensive review of empirical and dynamic wildfire simulation models, focusing on their applications in predicting bushfire and wildfire spread across Australia (Singh et al., 2025). It critically evaluates a suite of simulation systems including PHOENIX Rapidfire, SPARK, AUSTRALIS, REDEYE, IGNITE, and SiroFire, each leveraging distinct modeling techniques to simulate fire behavior, together with a variety of traditional machine learning and deep learning methods for wildfire prediction. PHOENIX Rapidfire, a deterministic simulator, uses a fire characterization model based on Huygen's principle to predict spread, flame height, and intensity. While it excels in speed and ease of use, it is limited by reliance on predefined behavior models and underestimation of irregular fire shapes (Pugnet et al., 2013; Richards, 1995). SPARK provides flexible, modular simulation driven by user-defined spread models and integrates well with GIS platforms, though its high computational demands pose practical constraints. AUSTRALIS employs a discrete-event simulation based on empirically derived rate-of-spread models; despite its efficiency, it underperforms in severe fire conditions (Miller et al., 2015). REDEYE and IGNITE integrate geospatial and real-time data for risk prediction and hotspot mapping, respectively, yet their effectiveness is limited by data compatibility and platform-specific requirements. SiroFire models dynamic weather components and supports strategic planning but lacks adaptability for diverse fuel types (Singh et al., 2025). Collectively, these simulators provide valuable predictive capabilities; however, each exhibits distinct limitations, ranging from computational inefficiencies and limited model adaptability to reduced accuracy under extreme conditions. This review highlights the need for hybrid modeling approaches that integrate traditional simulation techniques with machine learning and real-time data to enhance predictive accuracy, reduce simulation runtime, and strengthen operational resilience.

2.2. *Deep Learning in Wildfire Prediction*

Several prior studies have conducted comprehensive reviews of machine learning models, including deep learning approaches, for wildfire prediction. In this work, we concentrate on the most recent literature review to provide an up-to-date overview of the deep learning models utilized and their respective application domains. As the application of machine learning and deep learning to wildfire prediction has already been extensively discussed and explored in numerous review papers over the past decades, this paper does not repeat those reviews. Instead, we focus specifically on reviewing, examining, and summarizing studies that apply emerging generative AI models, an area that has not been comprehensively covered in previous reviews.

In the following subsection, we leverage a LLM to generate a literature summary and bibliographic visualizations that highlight the evolving trends in deep learning applications over time. Jain et al. (2020) presents a comprehensive scoping review of machine learning (ML) applications in wildfire science and management, analyzing 300 studies published up to the end of 2019. ML usage is categorized across six core domains: fuel characterization, fire detection, climate interactions, risk prediction, fire behavior, and post-fire effects. Among modern approaches, deep learning (DL) algorithms have shown strong potential for modeling wildfire spread, particularly due to their capacity to handle high-dimensional and multivariate data. Convolutional Neural Networks (CNNs) are widely used for spatial fire detection and smoke recognition from imagery, while Long Short-Term Memory (LSTM) networks incorporate temporal dynamics to model fire growth. Deep Neural Networks (DNNs) have also been applied to map burned areas and forecast fire spread, often outperforming traditional models when sufficient annotated data are available. Despite their promise, the review emphasizes the importance of domain expertise and high-quality data for meaningful DL integration in operational forecasting.

A recent study systematically reviews deep learning (DL) applications in forest fire prediction, analyzing 55 key publications from 2017 to 2024 (Mambile et al., 2024). The review emphasizes the transformative role of deep learning in capturing complex spatiotemporal patterns associated with fire ignition and spread, offering significant advantages over traditional machine learning approaches. CNNs are effectively used for analyzing satellite imagery to detect fire-prone areas and assess post-fire damage. LSTM and Gated Recurrent Unit (GRU) networks model time-series data to forecast fire progression based on historical environmental conditions. Emerging generative AI models such as GANs have been used for synthetic data generation, while Multilayer Perceptrons (MLPs) and U-Net architectures support fire risk estimation and boundary segmentation. Despite promising results, DL models face challenges such as data heterogeneity, limited inclusion of human activity factors, generalization across geographies, and the scarcity of high-quality labeled datasets. These limitations highlight the need for integrating diverse data sources and establishing standardized evaluation protocols to ensure model reliability in real-world wildfire prediction scenarios.

2.3. *Limitations of the Existing Deep Learning Applications in Wildfire Prediction*

Based on a comprehensive review of existing literature at the intersection of deep learning and wildfire prediction, as well as an analysis of the inherent challenges and limitations of various deep learning models stemming from their underlying mechanisms and data-driven assumptions, we identify several critical knowledge gaps and challenges that constrain the effectiveness and broader applicability of current deep learning approaches in wildfire prediction.

L1. Quantification of Limited Uncertainty: Traditional models such as CNNs and RNNs typically produce deterministic outputs and struggle to quantify prediction uncertainty, an essential capability for wildfire management and emergency response applications involving stochastic environmental processes, such as abrupt changes in wind speed and directions (Gal and Ghahramani, 2016; Lakshminarayanan et al., 2017).

L2. Weak Long-Term Dependency Modeling: Recurrent Neural Networks (RNNs) and Deep Neural Networks (DNNs) often struggle with vanishing gradients and limited temporal memory, which undermines their ability to capture long-range dependencies. This limitation makes them less effective in modeling the temporal progression of wildfires and in representing the long-term variability of underlying environmental processes such as fuel accumulation, climate patterns, and vegetation dynamics (Hochreiter et al., 2001; Chen et al., 2024).

L3. Inadequate Multimodal Data Integration and Prediction: Traditional deep learning architectures are not inherently designed to fuse multimodal data sources, such as 2D GIS data (e.g., satellite imagery, fuel load maps, and meteorological data) and 3D point clouds (e.g., digital terrain models) (Li et al., 2022). As a result, generating multimodal fire spread prediction outputs across different dimensions—from 1D time series to 3D spatial representations—within a unified deep learning framework remains a significant challenge.

L4. Limited Data Augmentation Capabilities: Traditional deep learning models, such as CNNs and RNNs, typically achieve strong performance only when trained on abundant, high-quality labeled data. They depend heavily on large volumes of annotated samples, which are often scarce in wildfire prediction tasks due to the rare, unpredictable, and spatially heterogeneous nature of fire events (Ghali and Akhloufi, 2023; Xu et al., 2024f). However, many of these models lack the capability to perform data augmentation or generate synthetic training samples, limiting their predictive accuracy and generalizability in data-sparse or unseen regions. This limitation poses a significant challenge for developing robust wildfire.

L5. Missing Data and Poor Data Quality Challenges: Environmental datasets frequently contain missing or incomplete information caused by sensor malfunctions, occlusion from cloud cover in satellite imagery, or data transmission failures (Shen et al., 2015). Such data gaps hinder accurate modeling and prediction. Traditional deep learning models often assume complete input data or rely on simplistic imputation methods that fail to capture the underlying spatiotemporal dependencies critical for wildfire dynamics. These limitations reduce model robustness and prediction accuracy in real-world scenarios where data is inherently noisy or sparse (Li et al., 2020).

L6. Lack of Explainability: Deep learning models such as CNNs and RNNs often operate as "black boxes," providing limited insight into how predictions are made and offering little transparency or trustworthiness (Rudin, 2019; Doshi-Velez and Kim, 2017).

While previous studies have provided structured and comprehensive reviews, most recent research remains focused on traditional machine learning and deep learning methods, or at most covers only a specific type of generative AI model for wildfire prediction. In contrast, comprehensive reviews and in-depth discussions that encompass the broader spectrum of emerging generative AI models, along with explanations of their underlying algorithmic principles in this domain, remain scarce and largely underexplored.

In the following section, we examine recent emerging studies that apply generative AI models to wildfire spread prediction, discussing the underlying rationale for using generative approaches and highlighting their advantages over traditional deep learning methods in addressing the aforementioned limitations. Our discussion then expands to explore how popular generative AI models can outperform conventional deep learning approaches in certain predictive analytics tasks. Ultimately, we aim to offer new perspectives on the potential of generative AI in next-generation emergency response systems, enabling faster, more reliable, and higher-resolution predictions of wildfire spread.

3. Emerging Generative AI Models and Their Advantages

Since around 2018 and especially in the early 2020s, generative AI models have experienced rapid advancements and widespread adoption across diverse fields, marking a significant shift in the landscape of artificial intelligence (Brown et al., 2020). Broadly defined, generative AI refers to a class of machine learning models that are capable of learning the underlying distribution of data and generating new, realistic content—such as text, images, audio, or even simulations—that resembles the training data (Goodfellow et al., 2014; Kingma et al., 2013; Ho et al., 2020). These models and their architectures have been increasingly experimented with and adopted to solve complex problems across various scientific disciplines.

3.1. Generative AI Applications in Environmental and Urban Sciences

The recent emerging generative AI models go beyond traditional predictive analytics by creating novel outputs, making them highly valuable in data-scarce environments or in domains requiring scenario generation, synthesis, or simulation. Generative AI encompasses several prominent categories, including GANs, VAEs, Autoregressive Models (AR), Diffusion Models, and Flow-based Models (Rezende & Mohamed, 2015; Vaswani et al., 2017; Kingma & Dhariwal, 2018). Within these categories, more specialized types have emerged: GANs consist of a generator and discriminator in adversarial training to synthesize realistic data (Goodfellow et al., 2014); VAEs combine probabilistic encoding and decoding for efficient latent space learning (Kingma et al., 2013); autoregressive models like GPT-4 predict future tokens in sequences for high-quality text generation (Brown et al., 2020); diffusion models such as Stable Diffusion and denoising diffusion probabilistic models (DDPMs) generate content by gradually denoising random noise into coherent samples (Ho et al., 2020; Rombach et al., 2022); and flow-based models leverage invertible transformations for exact likelihood estimation and sample generation (Dinh et al., 2017).

Each generative AI model and its architecture offers distinct mathematical properties and advantages depending on the application context. The rise of these models has revolutionized data science and AI by enabling machines to not only interpret and predict but also to imagine and create, thereby unlocking new opportunities across fields including hazard prediction, urban planning, climate science, decision support, design automation, and digital twin construction (Xu et al., 2024c; Ma et al., 2024). In the environmental hazard domain, Ma et al. (2024) presents a comprehensive review of how generative AI addresses longstanding challenges in data availability, quality, and resolution. These models learn high-dimensional probability distributions from limited samples, making them ideal for data-scarce applications such as geohazards, hydrometeorology, and climate-related analysis. By generating physically consistent synthetic data—ranging from downscaled meteorological fields to simulated landslide and seismic imagery—GenAI enhances forecasting accuracy, susceptibility mapping, and early warning systems, driving more reliable and scalable hazard modeling frameworks. In the urban management sector, Xu et al. (2024c) conducts a scoping review on integrating GenAI into urban digital twins, highlighting its transformative role in automating the generation of high-quality urban data, hypothetical planning scenarios, and 3D city models. These capabilities help overcome major challenges related to data sparsity, simulation scalability, and design complexity. Through the synthesis of multi-modal urban data and simulation of complex dynamics, GenAI enhances real-time decision support, predictive analytics, and participatory planning across sectors such as transportation, energy, water, and infrastructure. The convergence of GenAI with digital twin technologies represents a paradigm shift toward intelligent, adaptive, and inclusive urban solutions. Furthermore, growing research extends GenAI applications into other urban subsystems, including logistics optimization, intelligent transportation systems, and domain-specific knowledge generation (Tupayachi et al., 2024; Xu et al., 2024e; Taiwo et al., 2025).

3.2. Advantage over Traditional Deep Learning Models

Building on the limitations identified in the existing wildfire prediction literature, we conducted a comparative analysis of traditional deep learning models and generative AI approaches. As summarized in Section 2.3, our findings underscore the key advantages of generative AI models in addressing the constraints of conventional methods. These advantages are outlined in the list below, and a detailed comparison is provided in Table 3, which maps each limitation (L1–L6) discussed in Section 2.3 to corresponding strengths of generative AI.

Richer Uncertainty Modeling: In contrast to many traditional deep learning models, generative AI models such as VAEs and diffusion models produce probabilistic outputs that inherently capture uncertainty in predictions—an essential capability for high-risk applications like wildfire forecasting (Kingma et al., 2013; Ho et al., 2020). This feature can be leveraged to address the limitation L1.

Table 2: Comparison of Traditional Machine Learning, Deep Learning, and Generative AI models.

Feature	**Traditional ML** (e.g., SVM, RF)	**Deep Learning** (e.g., CNN, LSTM)	**Generative Deep Learning** (e.g., VAE, GAN, Transformer, Diffusion)
Data Generation Capability	Cannot generate data	Predictive only	Can generate new, realistic, diverse data
Representation Learning	Manual feature engineering	Learns hierarchical features	Learns latent and semantic representations
Handling Missing Data / Imputation	Basic imputation (e.g., mean)	Regression-based or interpolation only	Learns to impute based on data distribution
Few-shot / Zero-shot Learning	Requires full training	Requires full training	Supported by large-scale transformers
Multimodal Learning	Needs manual integration	Separate networks for each modality	Unified models handle text, image, video, etc.
Uncertainty Quantification	Via Bayesian methods or ensembles	Deterministic output	Built-in probabilistic frameworks (e.g., VAEs)
Synthetic Data Augmentation	Not supported	Requires manual engineering	Easily supports realistic data generation
Scenario Simulation	Not applicable	Not applicable	Simulates realistic and hypothetical conditions
Latent Space Manipulation	Not available	Not interpretable	Supports interpolation and control
Creativity & Generative Power	None	None	High—generates novel outputs and scenario
Data Efficiency	Needs many labeled samples	High data demand	Some support few-shot learning via pretraining
Interpretability	Often interpretable	Difficult to interpret hidden layers	Latent space can be visualized and interpretable
Training Complexity	Simple to train	Needs tuning and GPU support	Complex training and high computational cost
Use in Scientific Simulation	Limited (basic regression)	Used in some modeling	Strong in data-driven and uncertain modeling

Better Long-Term Dependencies: Transformer-based architectures outperform recurrent neural networks (RNNs) in modeling long-range dependencies in sequential data, making them well-suited for tracking wildfire dynamics over extended time periods (Vaswani et al., 2017; Brown et al., 2020) The capability could be harnessed to tackle the limitation L2.

Multimodal Data Fusion: Generative AI models, particularly those based on transformers and diffusion techniques, excel at integrating heterogeneous data sources (e.g., satellite imagery, meteorological variables, and point clouds), enabling more robust 2D and 3D wildfire forecasting through a unified framework (Rombach et al., 2022; Radford et al., 2021) to address the limitation L3.

Data Augmentation & Synthesis: Generative AI models such as GANs and diffusion models can produce synthetic yet realistic wildfire progression data, providing valuable training samples in data-scarce scenarios, facilitating missing data imputation to enhance data quality, and supporting the simulation of extreme or hypothetical conditions (Goodfellow et al., 2014; Dhariwal and Nichol, 2021). This capability can be leveraged to address Limitations L4 and L5, as well as to enable scenario generation for simulating hypothetical wildfire events.

AI Explainability through Latent Space: Many generative AI models, such as VAEs and GANs, rely on latent spaces and latent vectors to operate, where complex data relationships are encoded in lower-dimensional representations (Kingma et al., 2013; Goodfellow et al., 2014). These latent variables can be visualized and analyzed to enhance the explainability, interpretability, and trustworthiness of the models in tasks such as classification, prediction, clustering, and data generation (Xu et al., 2024a), thereby addressing Limitation L6.

The unique advantages of generative AI models are systematically inferred from their architectural principles and algorithmic rationale, particularly in the context of data-driven wildfire prediction. Applications of these models often rely on standard environmental and urban GIS datasets—such as shapefiles, raster imagery, and 3D LiDAR point clouds—which are also widely used in generative AI research across other domains. In Section 5, we present a comprehensive and critical review of studies applying generative AI to wildfire prediction, highlighting their strengths for bushfire management. Our subsequent review of generative AI models aims to explore future opportunities for leveraging their strengths to revolutionize bushfire prediction, as well as to discuss the associated challenges. The insights gained from this review are presented in Section 6.1.

4. Review Strategy and Methodologies

This study employs a human–AI collaborative approach by leveraging an automated pipeline powered by a LLM to systematically retrieve relevant research articles from multiple academic databases (Xu et al., 2024b). Guided by user-defined search queries, the system automates literature retrieval, characterization, and knowledge synthesis to generate bibliometric summaries. These summaries provide insights into how various machine learning algorithms, and more recently, generative AI models, have been applied to support fire spread prediction and propagation modeling, often in conjunction with complementary computing and informatics technologies.

To conduct a critical review of deep learning and generative AI , we developed a series of targeted search queries to perform a comprehensive literature review across both the IEEE Xplore and Scopus databases. Our search strategy was designed to address two primary objectives: first, to conduct a broad initial search that captures a wide spectrum of studies applying artificial intelligence and deep learning techniques to bushfire spread and propagation; and second, to narrow the focus by identifying recent and emerging research that specifically explores the use of generative AI models—such as VAEs, GANs, Transformers, and diffusion models—for wildfire prediction. The detailed search queries used for each phase of the review are presented in Figure 1.

4.1. LLM-Powered Literature Characterization

In addition to the identified articles, we utilized an LLM-powered tool developed in our previous work (Xu et al., 2024b) to characterize the literature by extracting taxonomies from each paper's abstract using a combined process of Scientific Discourse Tagging (SDT) and Named Entity Recognition (NER). These extracted taxonomies were then classified based on an existing body of knowledge. A bibliometric summary is presented in Figure 2, which visualizes the number of publications employing various machine learning and deep learning models. The models are grouped into three categories: traditional machine learning, deep learning, and generative AI, and are displayed as bar charts. Figure 3 presents a more detailed characterization and summary of the literature, mapping the number of publications that apply various categories and types of machine learning and deep learning models across different wildfire prediction application areas over the years. The classification of the literature is conducted using Sentence Transformers, which align the extracted taxonomy from each article with the existing body of knowledge (Xu et al., 2024b). This alignment is performed using a cosine similarity threshold that compares the literature-derived taxonomy with named entities and definitions defined in a domain ontology, which was constructed based on comprehensive literature reviews and authoritative textbooks. In this study, a cosine similarity threshold of 0.7 is used to ensure reliable knowledge alignment, allowing literature to be classified under a specific methodology or application area only when its extracted taxonomy is highly semantically relevant to a corresponding definition in the existing body of knowledge.

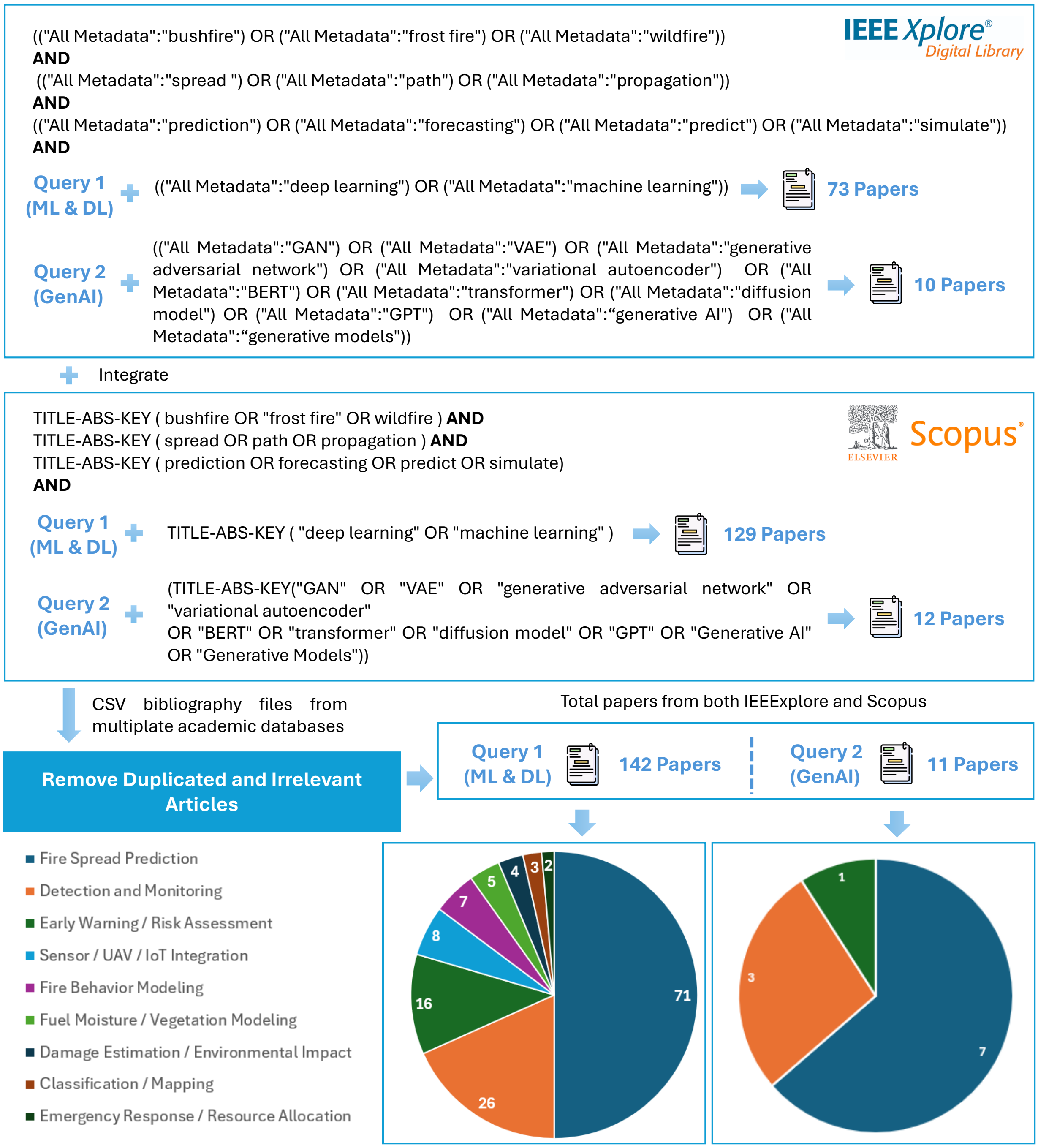

Figure 1: Search queries used to identify and acquire literature from IEEExplore and Scopus databases.

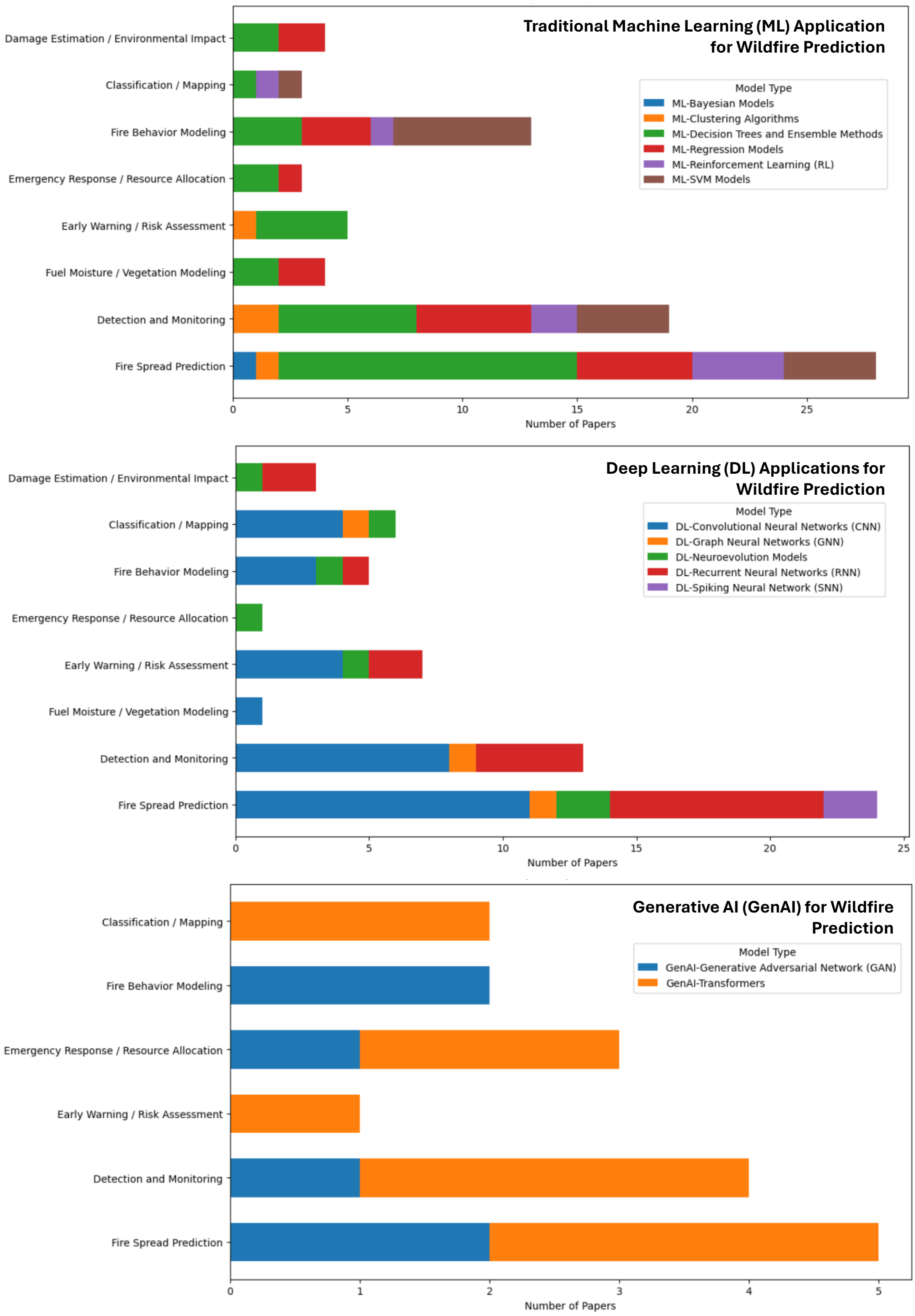

Figure 2: Distribution of literature counts across various machine learning and deep learning model types, categorized by application areas. The analysis was conducted using an LLM-powered research tool.

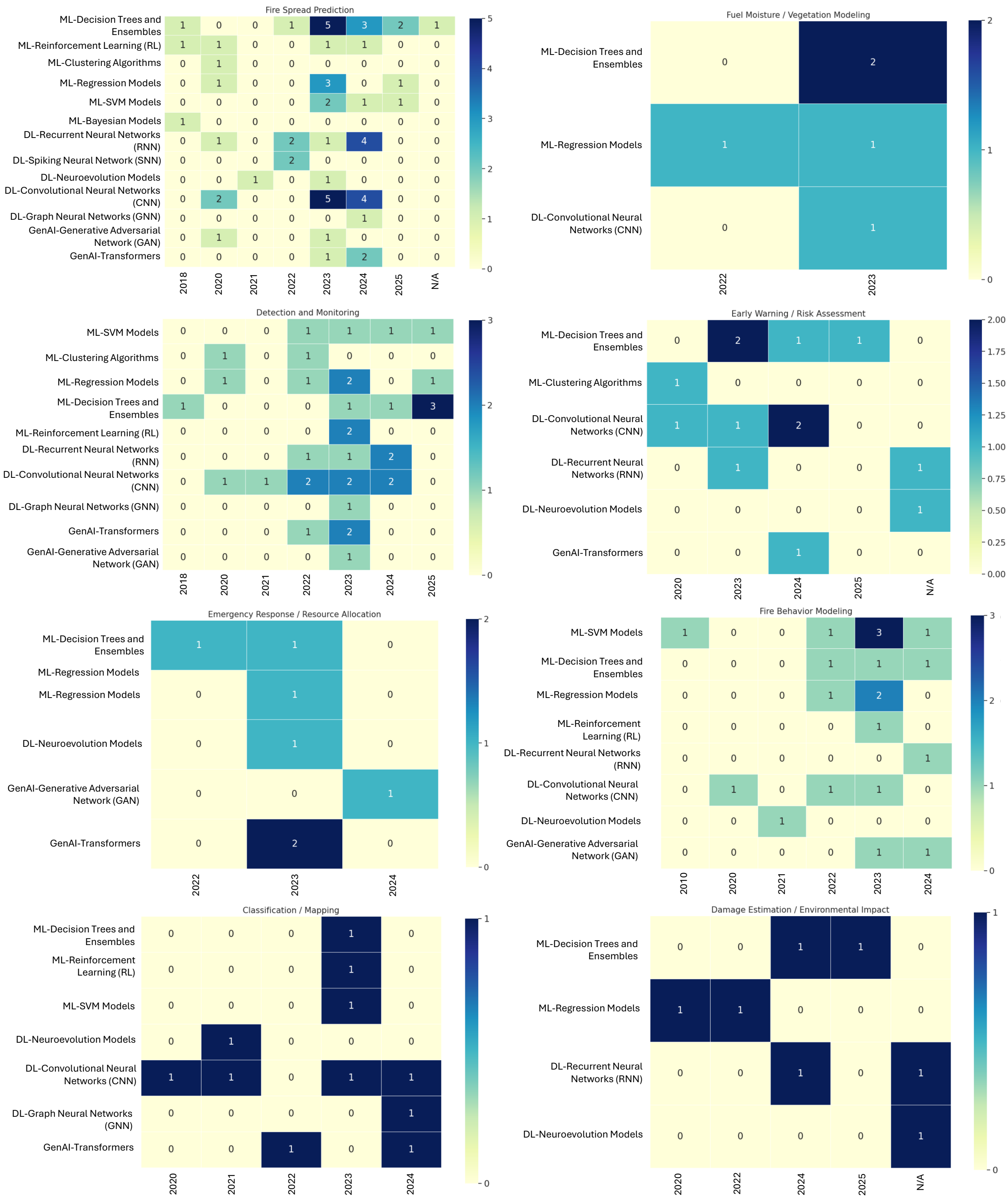

Figure 3: Classification of existing deep learning literature in wildfire science by model type, application area, and publication year, generated using an LLM-powered research tool.

Based on our bibliometric summary of articles retrieved from IEEE Xplore and Scopus using a general generative

AI query, we find that applications of generative AI in wildfire prediction remain limited, primarily focusing on GANs and transformers, as shown in Figure 3. Although other generative models could similarly analyze or synthesize relevant environmental data, this gap highlights significant opportunities for future research in the field.

5. State-of-the-Art Generative AI Applications in Wildfire Management

This section provides an in-depth review of current applications of generative AI in the wildfire prediction domain. The literature discussed is drawn from a refined subset of 17 research articles identified through IEEE Xplore and Scopus queries, as illustrated in Figure 1. The refinement process focuses on selecting studies that employ generative AI models as the core research methodology for wildfire-related analysis, rather than those using generative models solely for generic data processing or preprocessing tasks. Beyond the LLM-powered literature characterization, we also conducted a manual review and validation to filter out 1 research articles that claimed to use generative AI based on general rationale, but did not actually implement any generative AI models or architectures. Another 3 articles were founding using the diffusion models from the environmental science sector, rather than using the stable diffuser, which is one type of generative AI models. In addition, we also manually examined and removed 1 article from the initial selection that is retracted by the journal.

Through the following subsections, we conduct a structured and in-depth review on 11 existing studies that have explored the use of generative AI models for wildfire management.

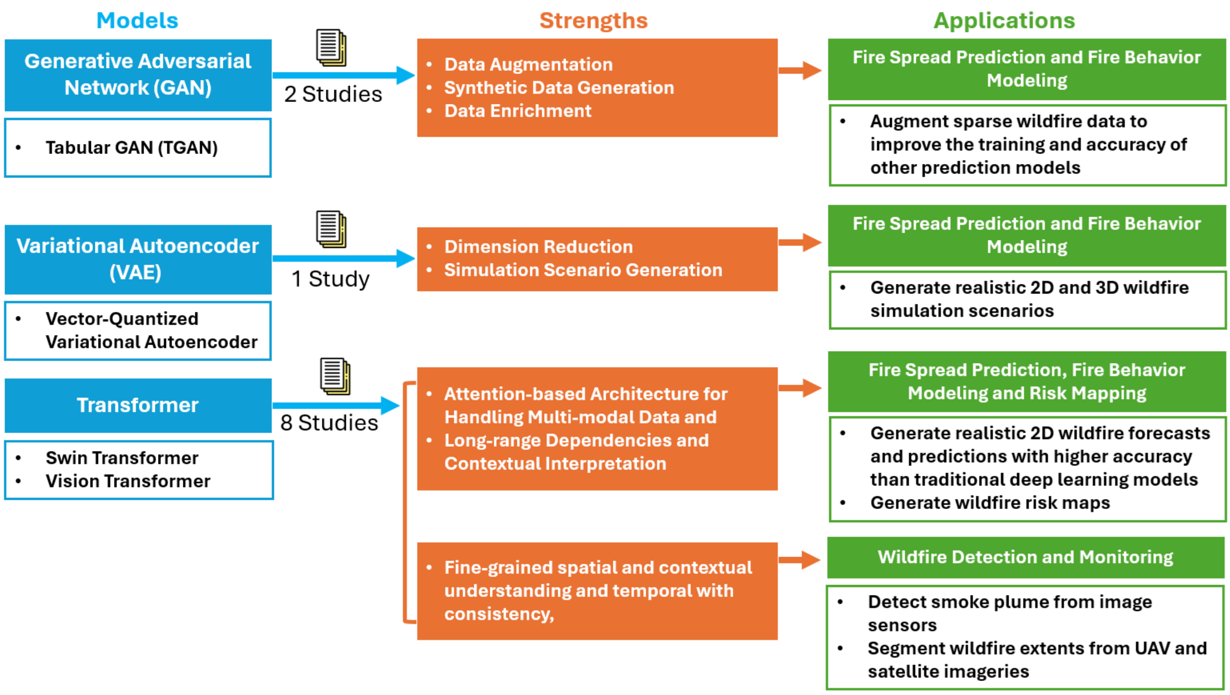

Figure 4: Summary of recent studies applying generative AI to diverse areas in bushfire modeling and prediction.

5.1. *Fire Spread Prediction and Fire Behavior Modeling*

We identified seven existing studies that have explored or prototyped the use of various generative AI models to support fire spread prediction and fire behavior modeling. These studies leverage different architectures, including GANs, VAEs, and generative transformers, to simulate wildfire dynamics, generate synthetic fire scenarios, or enhance predictive performance. Collectively, they demonstrate the emerging potential of generative AI in capturing the complex spatiotemporal patterns of wildfire propagation and improving the accuracy, scalability, and adaptability of fire behavior forecasting systems.

5.2. *Generative Adversarial Network (GAN)*

GANs and their variants have proven valuable in environmental and urban research by generating synthetic data to augment limited and imbalanced datasets (Xu et al., 2024c). This capability is especially critical in wildfire research, where collecting real-world fire data is often constrained by safety risks, high costs, and logistical challenges. By simulating underrepresented fire scenarios—such as passive and active crown fires—GANs help improve the diversity and robustness of training data, leading to more accurate classification of fire behavior and better support for operational decision-making. We identified two studies that effectively employ GANs for data augmentation to enhance wildfire spread prediction through integration with machine learning and simulation models.

Khanmohammadi et al. (2023) presents a machine learning framework for predicting wildfire spread sustainability and crown fire occurrence in semiarid shrublands of southern Australia. The study uses a TGAN to generate synthetic fire records, addressing the challenge of small training datasets commonly encountered in this domain. The inclusion of synthetic data led to substantial performance improvements, increasing classification accuracy by up to 20% for spread sustainability and 4% for crown fire prediction. This enhanced dataset was used to train and evaluate several classifiers—including Support Vector Machines (SVM), Multilayered Neural Networks (MLP), and Multinomial Naive Bayes (MNB)—with the SVM model paired with TGAN-generated data achieving the highest accuracy. The results demonstrate the potential of combining generative AI with traditional supervised learning models to improve generalization and reliability in data-scarce wildfire prediction settings. Khanmohammadi et al. (2024) extends this approach to Canadian conifer forests, focusing on predicting wildfire propagation types, including surface, passive crown, and active crown fires. In this study, TGAN is again employed to address class imbalance by generating synthetic data for underrepresented fire types, significantly boosting prediction accuracy and F1-scores—especially for difficult-to-classify categories like passive crown fires. The study evaluates four additional machine learning models: two ensemble methods (Random Forest and XGBoost) and two AutoML approaches (TabPFN and AutoGluon), with TabPFN consistently achieving the best results when trained on GAN-augmented data. These findings reinforce the value of GAN-based data generation as a means of overcoming real-world data limitations and enhancing the predictive capabilities of wildfire behavior models.

5.2.1. *Variational autoencoder (VAE)*

The use of VAEs and their variants is emerging in the wildfire prediction sector to generate realistic spatiotemporal simulations of fire spread, serving as synthetic training data for downstream forecasting models. These generative models are particularly effective for tasks that require the synthesis of physically consistent fire evolution sequences from high-dimensional, multi-modal inputs, such as topography, vegetation density, and weather conditions, where real data may be scarce, incomplete, or expensive to obtain through traditional physics-based simulations.

Cheng et al. (2023) presents a generative AI framework aimed at improving spatial-temporal wildfire nowcasting by addressing the limitations of traditional physics-based simulation methods, which are often computationally intensive and time-consuming. The authors propose the use of a Vector-Quantized Variational Autoencoder (VQ-VAE) to generate high-fidelity, physically realistic sequences of burned area evolution in wildfire scenarios. The generative model is trained on synthetic data from a Cellular Automata (CA) simulator and used to produce 3D fire spread sequences with temporal and spatial consistency. This approach significantly accelerates data generation, achieving a speed-up of over four orders of magnitude compared to CA and MTT simulations—while capturing critical geophysical dependencies such as vegetation density and slope. The generated wildfire scenarios serve as training data for a machine learning surrogate model combining Proper Orthogonal Decomposition (POD) and a Long Short-Term Memory (LSTM) network to emulate fire dynamics. The use of VQ-VAE addresses key challenges in the domain, including the high computational cost of simulation, the need for large volumes of training data, and the ability to simulate new, realistic wildfire events that reflect observed behavior. The inclusion of VQ-VAE–generated data improved the surrogate model's prediction accuracy and structural similarity scores on both simulated and real wildfire events, demonstrating the effectiveness of generative AI in enhancing the resolution, efficiency, and generalizability of wildfire forecasting systems.

5.2.2. *Transformer*

Transformers have emerged as powerful deep learning architectures for wildfire prediction tasks, particularly in modeling fire spread, classifying risk levels, and generating predictive spatial outputs from complex spatiotemporal data. Their capacity to capture long-range dependencies and contextual interactions across diverse input modalities, such as satellite imagery, weather data, topography, and vegetation maps—makes them especially well, suited for wildfire forecasting tasks that require spatial precision and temporal consistency to support timely decision-making and emergency response.

Li and Rad (2024) presents a transformer-based hybrid model—Attention Swin U-Net with Focal Modulation (ASUFM)—designed for next-day wildfire spread forecasting across North America. ASUFM integrates spatial attention and focal modulation layers into a Swin Transformer U-Net backbone, producing predictive fire masks from multivariate remote sensing data. Though not a conventional generative model, ASUFM simulates realistic fire spread scenarios and addresses challenges such as spatial resolution, class imbalance, and temporal consistency. Trained on an expanded NDWS dataset (2012–2023), the model achieved state-of-the-art results in Dice score and PR-AUC, outperforming U-Net and other transformer variants. Additional techniques, including weighted loss functions, skip connections, and cosine learning rate scheduling, further enhanced the model's generalization and accuracy. Deepa et al. (2024) proposes a contrastive learning framework for early forest fire prediction that combines a Contrastive Vision Transformer (CViT) with a Pool Former module. CViT functions as a powerful feature extractor via self-supervised contrastive learning and multi-head attention, while the Pool Former improves prediction efficiency by modeling spatial dependencies without heavy matrix operations. Though it does not employ traditional generative AI, the framework enhances feature robustness under variable environmental conditions through preprocessing and data augmentation strategies. The model achieved competitive performance, with 92.8% accuracy and an F1-score of 90.2%, surpassing multiple baseline models including CNN, RNN, Faster R-CNN, and ResNet. Annane et al. (2024) introduces a real-time wildfire prediction system that integrates a CNN–Transformer hybrid model with a blockchain-based infrastructure for enhanced data security and traceability. The CNN extracts spatial features from drone imagery, while the transformer captures temporal patterns such as smoke visibility and fire direction. Although it does not use generative AI in the traditional sense, the system generates fire probability maps that simulate the spread and severity of wildfires, improving alert accuracy and resolution. It also incorporates a rule-based assistant for decision support and achieves 93.18% prediction accuracy, outperforming CNN and ResNet-42 models, albeit with a slightly higher training time. In contrast, Li et al. (2024b) presents a true generative AI approach through the development of Sim2Real-Fire, a large-scale, multi-modal dataset paired with the S2R-FireTr transformer model. S2R-FireTr forecasts and backtracks binary fire masks by learning from 1 million simulated wildfire sequences and generalizing to 1,000 real-world cases. By leveraging cross-attention across five aligned modalities—topography, vegetation, fuel types, weather, and satellite imagery—it generates physically plausible fire spread scenarios even under temporally incomplete conditions. Outperforming physical simulators and deep learning baselines in both AUPRC (72.9%) and F1-score (69.6%), S2R-FireTr significantly reduces simulation time while maintaining high spatial-temporal fidelity. This work exemplifies the transformative potential of generative AI in enabling rapid, scalable, and low-cost wildfire scenario generation for both predictive and forensic applications.

5.3. Wildfire Detection and Monitoring using Vision Transformers

Generative AI models, particularly vision transformers, are increasingly utilized in wildfire monitoring to generate high-resolution segmentation masks and predictive spatial representations of fire spread. These models excel in tasks requiring fine-grained spatial understanding and temporal consistency, such as detecting smoke plumes and segmenting active fire zones, due to the visual complexity of input data (e.g., RGB UAV imagery, thermal maps) and the operational need for accurate, real-time predictions to support early firefighting efforts. Our review identified three notable studies that incorporate transformer-based architectures to facilitate wildfire detection and monitoring.

Falcão et al. (2023) focuses on early detection of wildfire smoke plumes using a deep learning ensemble framework that integrates EfficientNetV2 (CNN), DeiT, and Swin TransformerV2 (both vision transformers). While generative models are not explicitly employed, the ensemble architecture—coupled with a neural network-based metaclassifier—demonstrates strong performance under challenging conditions like haze, fog, and low-contrast smoke. The study leverages transfer learning and data augmentation techniques to improve generalization, achieving an average accuracy of 96.46% and an AUPRC of 95.14%, highlighting the value of architectural diversity in image-based wildfire surveillance. Ghali et al. (2022) targets fire classification and segmentation using UAV imagery. Although it does not incorporate conventional generative AI, the framework produces fine-grained segmentation masks, effectively achieving a generative outcome. The authors develop an ensemble classifier with EfficientNet-B5 and DenseNet-201 for fire detection and employ three segmentation models—EfficientSeg, TransUNet, and TransFire—two of which are transformer-based. These models address complex challenges such as detecting small fires and delineating fire boundaries in noisy, cluttered backgrounds. TransUNet-R50-ViT outperforms CNN-based baselines on the FLAME UAV dataset, achieving an F1-score of 99.9%, confirming the efficacy of vision transformers in high-resolution fire segmentation. Ghali et al. (2021) explores the use of vision transformers—TransUNet and Medical Transformer (MedT)—to segment wildfire regions from RGB imagery for early detection and boundary delineation. These transformers perform generative tasks by producing binary segmentation masks that can be used to simulate wildfire spread scenarios. The models address core challenges such as fine boundary detection, long-range dependency modeling, and feature misclassification. Trained on the CorsicanFire dataset, TransUNet and MedT achieve F1-scores of 97.7% and 96.0% respectively, outperforming conventional architectures like U-Net, U2-Net, and EfficientSeg. Despite slightly longer inference times (1.2s for TransUNet and 2.72s for MedT), the trade-offs are justified by improvements in spatial granularity, generalization, and robustness under diverse environmental conditions.

5.4. Wildfire Risk Mapping using Transformers

Wildfire risk mapping plays a critical role in proactive fire management, enabling early warning systems, resource allocation, and strategic response planning across vulnerable landscapes. In recent years, transformer-based deep learning models have emerged as powerful tools for this task, offering scalable and data-efficient solutions for generating accurate and spatially coherent fire risk forecasts.

Limber et al. (2024) developed an intelligent tool to forecast wildfire potential across California by emulating the Wildland Fire Potential Index (WFPI) using a deep learning architecture based on a residual transformer model. The key application area is short-term wildfire risk prediction over large geographic regions, with the goal of improving early warning capabilities for fire management and emergency response. The authors trained the transformer to generate daily WFPI maps using input variables including Daymet meteorological data, MODIS-derived NDVI, and static land fuel classifications from the Scott and Burgan fire behavior fuel models. In this study, the transformer functions as a generative forecasting emulator, producing new spatial fire risk scenarios up to seven days ahead. This model addresses critical challenges in wildfire modeling, including the high computational cost of physical models, and the need for rapid, spatially coherent fire potential forecasts. The residual connection within the transformer leverages temporal autocorrelation in past WFPI values, improving accuracy and stability over short-term forecasts. Notably, the model achieved spatial correlation coefficients ranging from 0.85 to 0.98 across four weekly forecasts in July 2023, demonstrating its effectiveness. The study also incorporated Bayesian hyperparameter optimization to fine-tune the transformer and leveraged high-performance computing resources to efficiently train and evaluate the model. Although no other machine learning models were directly compared, the transformer significantly improves forecast speed and quality relative to existing USGS/USFS WFPI generation methods, highlighting the potential of transformer-based architectures for scalable, data-driven wildfire risk prediction.

6. Visions and Challenges

Generative AI offers a transformative approach to wildfire prediction and management, enabling advanced simulation and analysis of complex fire dynamics. To fully realize its potential, however, several scientific, technical, and operational challenges must be addressed. This section outlines our vision for generative AI in wildfire applications and discusses key barriers to its scalable, trustworthy, and practical deployment.

6.1. New Opportunities with Diverse Generative AI Architecture

Our review finds that current generative AI applications in bushfire prediction mainly rely on GANs, VAEs, and Transformers (Goodfellow et al., 2014; Kingma et al., 2013; Vaswani et al., 2017). However, other architectures—such as Deep AR, Flow-based, Diffusion Models, and Auto-Regressive Transformers—remain underexplored despite their potential to improve wildfire spread prediction, emergency response, and management optimization through more accurate, diverse, and interpretable spatiotemporal scenario generation (Ho et al., 2020; Papamakarios et al., 2021).

Deep AR Models are a class of generative AI models that generate data sequentially, with each output element conditioned on previously generated elements. This autoregressive property enables them to effectively capture temporal and spatial dependencies in sequential data. In the context of image and spatiotemporal modeling, PixelRNN and PixelCNN are notable examples that extend AR principles to two-dimensional data. PixelRNN employs recurrent neural networks to model the distribution of pixels row by row. They are often used for satellite imagery analysis and Super-resolution (Yang et al., 2019). PixelCNN uses convolutional architectures to achieve similar goals with improved parallelism. Both models generate pixels by conditioning on previously generated pixels, allowing for high-fidelity, structured output. These models have been used in previous studies to generate road, building, precipitation, and land cover maps (Song et al., 2021; Mohammad et al., 2022; Krapu et al., 2024; Wang et al., 2021)

These capabilities make PixelRNN and PixelCNN particularly well-suited for modeling the temporal dynamics and spatial evolution of wildfire progression, where the state at any given time or location depends heavily on prior conditions (Van Den Oord et al., 2016).

Flow-Based Models are a class of generative AI models that learn invertible transformations between simple base distributions (e.g., Gaussian) and complex data distributions through a series of bijective mappings. Unlike other generative AI models, flow-based models offer exact and tractable likelihood computation, making them particularly attractive for scientific applications requiring probabilistic interpretability. Notable examples include RealNVP (Dinh et al., 2017) and Glow (Kingma and Dhariwal, 2018), which use affine coupling layers and invertible 1x1 convolutions to enable efficient sampling and density estimation. Their ability to model high-dimensional, continuous variables with fine-grained control makes them especially well-suited for simulating geospatial variables such as fuel moisture content, temperature gradients, or wind vector fields—factors that are critical in wildfire behavior prediction. These models can learn complex, multivariate relationships directly from data while preserving physical consistency due to their invertibility and structure-preserving transformations.

Diffusion Models are a class of generative AI models that learn to generate data by reversing a gradual noising process. During training, data is iteratively corrupted by adding Gaussian noise, and the model learns to reverse this process step-by-step to recover the original input. This denoising diffusion process enables the model to capture complex data distributions with high fidelity. Notable examples include the Denoising Diffusion Probabilistic Model (DDPM) (Ho et al., 2020), which has demonstrated state-of-the-art performance in generating high-resolution, diverse images. Diffusion models are particularly well-suited for reconstructing missing data and generating plausible future environmental scenarios from noisy or sparse 2D inputs, such as satellite imagery or geospatial raster data. Their ability to progressively refine samples allows them to infer fine-grained spatial patterns and fill in incomplete observations with high accuracy, making them powerful tools for environmental modeling tasks like wildfire risk mapping or weather variable simulation.

Each generative architecture contributes distinct strengths to wildfire modeling. Autoregressive (AR) models are particularly effective for capturing temporal dependencies, making them well-suited for forecasting the sequential dynamics of fire movement over time (Limber et al., 2024). Flow-Based Models offer invertible mappings that preserve exact likelihoods, allowing them to model spatially continuous variables with high fidelity—ideal for representing terrain, fuel distribution, or meteorological gradients (Dinh et al., 2016; Kingma and Dhariwal, 2018). Diffusion Models, which have gained recent popularity, iteratively denoise sampled data to synthesize high-quality outputs such as 2D raster maps or geo-referenced images, enabling scenario-based simulation of fire evolution under diverse environmental conditions (Ho et al., 2020; Rombach et al., 2022). Finally, Auto-Regressive Transformers support the fusion and contextual learning of multiscale, multimodal data—such as weather, vegetation, topography, and sensor inputs, facilitating comprehensive, high-resolution prediction and decision support for wildfire risk assessment and management (Vaswani et al., 2017; Xu et al., 2024b).

Figure 5: A summary of five future visions for applying generative AI to revolutionize wildfire prediction and management, ranging from the development of multimodal 2D and 3D wildfire modeling to the implementation of cognitive digital twins with explainable AI capabilities.

6.2. *Visions for Generative AI-powered Wildfire Applications*

This section outlines a series of forward-looking visions for how generative AI, particularly in the form of foundation models, multimodal transformers, diffusion models, and LLM-based agents, can be harnessed to reshape wildfire prediction and management across scales and settings (as illustrated in Figure 5).

6.2.1. *Advancing Multimodal Approaches in 2D and 3D Wildfire Modeling*

Traditional wildfire modeling has primarily relied on 2D spatial datasets—such as satellite imagery, temperature maps, and vegetation indices. However, fire behavior is inherently three-dimensional, shaped by terrain elevation, vertical fuel distribution, atmospheric conditions, and urban infrastructure. Conventional deep learning approaches often handle 2D and 3D data in isolation, requiring separate models for different modalities, which limits integration and hampers model adaptability. The emergence of high-fidelity 3D fire spread modeling offers a transformative opportunity to improve emergency response, evacuation planning, and long-term mitigation (Moinuddin et al., 2024). By accounting for the vertical complexity of fire dynamics, 3D models enhance the accuracy of predictions related to fire pathways, temperature distribution, and ember dispersion, while also supporting immersive visualizations (Xu et al., 2023a).

Recent advancements in generative AI architectures, particularly VAEs and transformers, now allow for the development of unified multimodal models capable of processing geospatial, meteorological, and 3D structural data within a single framework. These models leverage shared latent representations and cross-modal attention to learn spatial, temporal, and structural patterns holistically. Unlike conventional systems that rely on fusing outputs from separate networks, this end-to-end generative approach improves maintainability, scalability, and adaptability. By embracing generative multimodal modeling, researchers and practitioners can move beyond fragmented workflows toward more cohesive, real-time predictive systems.

6.2.2. *Developing a Conversational Multi-Agent AI Assistant for Wildfire Prediction Using LLMs and RAG*

The integration of Large Language Models (LLMs) with Retrieval-Augmented Generation (RAG) offers a novel pathway for developing conversational multi-agent AI assistants for wildfire prediction. These systems can engage in multi-turn dialogue, retrieve domain-specific wildfire data, and generate context-aware, user-adaptive insights. Building on successful use cases in transportation and climate science (Xu et al., 2024e; Xie et al., 2025), this approach shifts wildfire intelligence from static interfaces to interactive, human-centered decision support. In this framework, specialized agents handle sub-tasks such as fire spread simulation, atmospheric analysis, or evacuation planning, coordinated by a dialogue manager driven by a fine-tuned LLM. RAG ensures the assistant's responses are not only generative but grounded in real-time data and scientific knowledge, drawing from sources like localized fire weather indices or historical ignition patterns (Xie et al., 2025).

This architecture enables natural language interaction for urban planners, emergency responders, and community members through an intelligent AI assistant capable of automatically retrieving relevant data, simulation outputs, and optimized solutions for decision support. It presents this information in an accessible, easy-to-understand format, providing non-technical users with tailored recommendations and real-time updates. Unlike traditional approaches that require manual data collection, technical expertise, and simulation execution, often resulting in outputs filled with domain-specific jargon that hinder interdisciplinary collaboration, the AI assistant offers a unified, scalable, and explainable interface. Continuously learning from expert feedback and new data streams, it supports adaptive wildfire intelligence. When embedded in smart city systems, such assistants foster more proactive, transparent, and inclusive fire risk assessment and emergency response.

6.2.3. Building an AI Foundation Model for Interdisciplinary Wildfire Management

The emergence of AI foundation models—large-scale, pre-trained systems built primarily on transformer architectures—has opened new possibilities for addressing complex, interdisciplinary challenges in environmental and urban domains (Li et al., 2024a; Myers et al., 2024). By nature, an AI foundation model is a large-scale, general-purpose model trained on diverse data to support a wide range of downstream tasks, serving as a flexible backbone for AI systems—not limited to any specific machine learning or deep learning technique (Li et al., 2024a). These models enable cross-domain knowledge transfer, zero-shot inference, and rapid fine-tuning, making them well-suited for high-impact applications such as wildfire prediction. A foundation model for wildfire management would leverage generative AI architectures, including LLMs and multimodal transformers, to learn from diverse datasets across spatial, temporal, and semantic dimensions. Trained on inputs such as satellite imagery, weather records, terrain data, fuel assessments, and fire incident reports, the model could generate predictive outputs and scenario-based simulations under varying conditions.

Unlike traditional models or task-specific deep learning pipelines, a generative foundation model offers a unified, adaptive, and scalable framework. Recent advancements in generative AI architectures—such as transformers, diffusion models, and autoregressive networks—have paved the way for developing multimodal AI models that seamlessly integrate diverse data sources, including satellite imagery, LiDAR, weather time series, textual reports, and both 2D and 3D spatial data. These models excel at capturing cross-modal relationships, enabling robust generalization across varied fire scenarios, geographic regions, and management tasks. Unlike traditional deep learning methods, such as CNN-based models specialized for 2D raster GIS data, AI foundation models for wildfire management harness the multimodal and multipurpose capabilities of contemporary generative architectures. This allows for the incorporation of evolutionary features utilizing both 2D and 3D data, along with other modalities, to not only enhance the accuracy of fire risk predictions across multiple dimensions but also support critical wildfire management tasks, such as detecting smoke, fire, and vulnerable vehicle and infrastructure from CCTV feeds, within a unified AI framework. Such an approach enhances the deployability, scalability, and maintainability of AI-powered systems in real-world applications.

6.2.4. Computationally Efficient Hypothetical Wildfire Scenario Generation on Edge Devices

Generative AI models such as VAEs and Transformers have emerged as computationally efficient surrogates for simulating wildfire spread and fire propagation. Unlike physics-based models that rely on intensive numerical solvers, these generative architectures can emulate spatiotemporal fire dynamics from historical or synthetic data, enabling the rapid generation of high-resolution wildfire scenarios with minimal computational overhead. Once trained, they deliver near-instant predictions, making them ideal for time-critical tasks such as emergency response, evacuation planning, and real-time firefighting operations. A key advantage of these models is their ability to run on edge devices—including UAVs, remote sensors, connected vehicles, and mobile platforms like tablets or smartphones used by firefighters. Prior work has shown that convolutional and transformer-based models can be optimized for execution on low-power hardware such as NVIDIA Jetson Nano or Intel Movidius, enabling on-board inference without cloud dependence (Hu et al., 2024; Mahdi and Mahmood, 2022). This reduces reliance on remote infrastructure and mitigates communication delays or outages, especially in remote or disaster-affected areas (Xu et al., 2024d).

These edge-deployable models also support decentralized computing, enabling scenario generation using **the most updated** real-time, field-collected data such as wind speed, terrain, vegetation, and humidity. Lightweight Vision Transformers (ViTs) and compact CNN-based fire segmentation algorithms are increasingly compatible with embedded systems, supporting high-frequency updates and real-time forecasting on resource-constrained devices (Spiller et al., 2022; Lee et al., 2024). This edge-oriented paradigm empowers frontline responders with on-the-fly fire modeling, delivering predictive fire trajectories, containment strategies, and dynamic risk maps—all processed locally. Embedded within mobile edge computing frameworks, these systems can continuously adapt to incoming sensor data, offering scalable, resilient, and connectivity-independent wildfire intelligence.

6.2.5. Interactive Wildfire Management through Explainable AI and Cognitive Digital Twins

Urban digital twins are dynamic virtual representations of physical city systems that integrate real-time data, simulations, and models to support planning, monitoring, and decision-making (Xu et al., 2024c; Weil et al., 2023). These digital twin technologies have been widely adopted across various smart city domains, including intelligent transportation systems, smart buildings, and environmental monitoring and management (Xu et al., 2023b; **?**; Diakite et al., 2022). Building upon this foundation, cognitive digital twins represent a new paradigm by embedding AI into digital twin frameworks to enhance their ability to learn, reason, and adapt (Zheng et al., 2022). Unlike conventional twins, cognitive digital twins integrate human-in-the-loop mechanisms to improve the trustworthiness, transparency, and interpretability of the decisions and predictions derived from underlying data models and simulations (Niloofar et al., 2023).

A key advantage of developing cognitive digital twins powered by generative AI is their ability to support explainable AI approaches, enabling these systems—often deployed as smart city apps or web platforms—to interact effectively with human users and enhance the supervision and interpretability of AI-generated results. Many generative AI models, such as VAEs and Transformers, rely on latent spaces and latent representations to encode complex data structures into compressed, abstract forms. These latent variables can be visualized and interpreted to reveal how models process information and generate predictions or classifications (Xu et al., 2024a; Liu et al., 2019). This capability is especially valuable in cognitive digital twin systems, where enhanced model explainability and interpretability are essential for ensuring accountability and transparency—particularly in time-critical emergency response scenarios such as wildfire spread prediction and risk forecasting (Abdollahi and Pradhan, 2023). In such applications, the multivariate feature space of complex environmental datasets can be encoded into a lower-dimensional latent space, enabling visualization and the extraction of meaningful patterns (Liu et al., 2019). Through interactive visualization and visual analytics, these insights can support a range of downstream tasks, including anomaly detection, decision support, and multivariate clustering for risk analysis and fire event characterization (Kwon et al., 2023; Xu et al., 2024a), and are essential for increasing the trustworthy of the prediction outcomes from generative AI models.

Meanwhile, the cyberinfrastructure supporting a digital twin can serve as an automated pipeline for integrating real-time environmental data from various sources, including sensors, unmanned aerial vehicles (UAVs), and crowdsourcing platforms. It also provides a cloud-based computing environment capable of hosting generative AI models developed for wildfire prediction. In this setting, diverse environmental data streams can be seamlessly ingested and processed by the AI models, ensuring that wildfire forecasts are generated using the most up-to-date information available.

Table 3: Challenges and potential solutions associated with applying generative AI models in wildfire prediction.

Challenge	**Description**	**Potential Solution**
Computational	Training and deploying large-scale generative AI models for wildfire prediction is resource-intensive due to high-resolution data demands, heavy memory usage, and slow inference.	Techniques such as quantization, low-bit training, distillation, and latent-space modeling can improve efficiency, though often at the cost of accuracy or interpretability.
Evaluation	Evaluating generative AI outputs is difficult due to the lack of standardized, interpretable, and domain-specific metrics for assessing the realism and utility of synthetic spatiotemporal fire scenarios.	Solutions include developing domain-specific and hybrid metrics, incorporating human-in-the-loop evaluation, uncertainty quantification, and physics-informed priors.
Energy and Environmental	Generative AI model development has a significant environmental impact due to high energy consumption and carbon emissions from large-scale training.	Mitigation strategies include model distillation, sparsity optimization, transfer learning, and adopting energy-efficient ”green AI” practices.

6.3. Challenges and Potential Solutions

Despite the promising potential of generative AI in wildfire prediction, several critical challenges must be addressed to ensure its reliability, scalability, and scientific validity in real-world fire management applications. Table 3 summarizes these key challenges along with potential solutions, which are further elaborated in the following subsections.

6.3.1. Computational Challenges

Training large-scale generative AI models—particularly diffusion models, transformers, and other autoregressive architectures—presents substantial computational challenges. These models typically require high-resolution spatial-temporal data spanning vast geographic regions and extended fire seasons, leading to massive, memory-intensive datasets. As emphasized by Manduchi et al. (Manduchi et al., 2024), training such models at scale demands access to powerful GPUs or TPUs, careful memory management, and optimization strategies to maintain training stability across distributed systems.

Moreover, inference with diffusion models often involves iterative denoising steps, while transformer-based language models follow a sequential token generation process, both of which result in high latency. This is particularly problematic in real-time or near-real-time wildfire forecasting applications where rapid decision-making is essential. Even recent improvements like FlashAttention and latent-space diffusion training (Manduchi et al., 2024; Bandi et al., 2023) only partially mitigate these bottlenecks. Additionally, robust training requires extensive data augmentation, domain adaptation, and fine-tuning, which further increases the computational burden (Bandi et al., 2023).

To improve computational efficiency, emerging strategies such as model quantization, low-bit training, distillation, and lossy latent-space modeling have shown promise (Manduchi et al., 2024). However, these approaches often come with trade-offs in terms of accuracy, robustness, or interpretability—making them challenging to adopt in high-stakes domains such as environmental hazard forecasting and disaster response.

6.3.2. Evaluation Challenges

Evaluating the outputs of generative AI models in wildfire prediction poses significant methodological challenges, particularly due to the lack of standardized, interpretable, and domain-specific evaluation frameworks. Unlike classification or regression tasks, where performance can be quantified using well-established metrics, the assessment of synthetic wildfire scenarios—especially those generated under creative or hypothetical conditions—remains highly subjective and context-dependent (Bandi et al., 2023; Manduchi et al., 2024). Widely used metrics such as Fréchet Inception Distance (FID) or Inception Score (IS), originally developed for image synthesis, are ill-suited for evaluating spatiotemporal fidelity, physical realism, or consistency with known fire behavior dynamics in environmental simulations (Bandi et al., 2023; Manduchi et al., 2024).

Recent studies emphasize the urgent need for developing "domain-specific evaluation metrics" tailored to complex generative tasks. These include assessing spatial spread accuracy, temporal progression, and physical plausibility relative to empirical wildfire data and simulation-based fire behavior models (Fui-Hoon Nah et al., 2023). Additionally, generative AI models frequently suffer from pathologies such as "mode collapse, sample hallucination, and memorization", which compromise their generalizability and reliability when trained on sparse or biased fire datasets (Manduchi et al., 2024). These issues are particularly critical in "high-stakes applications" such as real-time emergency response or predictive decision support, where misleading outputs can result in dangerous operational consequences.

The evaluation challenge is further exacerbated by the absence of ground truth for rare or extreme wildfire events, which limits model validation using traditional benchmarks. As Manduchi et al. (2024) and Sun et al. (2024) argue, current benchmarks fail to capture domain-specific constraints and interpretability, especially in dynamic, real-world environments. To address these shortcomings, researchers have advocated for the integration of "human-in-the-loop evaluation", "uncertainty quantification", and "physics-informed priors" into both model training and assessment pipelines (Yan et al., 2024; Fui-Hoon Nah et al., 2023). Furthermore, a growing body of literature calls for "hybrid metrics" that combine statistical quality measures with expert-driven assessments and simulation-based validations, offering a more holistic evaluation of generative outputs (Bandi et al., 2023; Manduchi et al., 2024; Fui-Hoon Nah et al., 2023).

6.3.3. Energy and Environmental Challenges

One significant but often under-discussed challenge in developing generative AI models for wildfire prediction lies in their substantial energy consumption and environmental footprint. Training foundation models—particularly those based on large-scale transformer architectures—requires extensive computational resources, often involving thousands of GPU hours and high-performance computing clusters (Zhou et al., 2024). This process results in considerable electricity usage, much of which is still powered by fossil fuels in many regions, leading to high levels of carbon emissions. As highlighted by Myers et al. (2024), the environmental cost of training a single large language model can surpass the annual carbon footprint of several individuals. While these models offer valuable capabilities for simulating fire dynamics and generating proactive mitigation strategies, their development raises important concerns regarding sustainability and ecological responsibility, especially in the context of wildfire prediction, where climate change and ecosystem degradation are already pressing issues.

To mitigate these impacts, it is essential to explore strategies such as model distillation, sparsity optimization, transfer learning from pre-trained models, and leveraging green AI principles that emphasize energy-efficient training and inference (Salehi and Schmeink, 2023; Barbierato and Gatti, 2024). Integrating these strategies not only aligns the development of AI models with climate-conscious values but also ensures that the tools designed to protect the environment do not inadvertently contribute to its degradation.

7. Conclusion

This paper advocates for a paradigm shift in wildfire prediction—from traditional physics-based and deep learning models to generative AI-driven approaches capable of real-time, high-resolution, and multimodal fire simulation. Through a comprehensive literature review and LLM-assisted bibliometric analysis, we highlight the strengths of emerging generative models—including VAEs, GANs, Transformers, Diffusion Models, and Flow-Based Models—in learning complex wildfire dynamics from heterogeneous, sparse, and incomplete datasets. These models offer enhanced scalability, probabilistic forecasting, and the capacity to simulate fire spread across both 2D and 3D spatial domains, effectively capturing large-scale patterns embedded in observational and simulated data. We further explore three key innovations: (1) the development of interdisciplinary AI foundation models that integrate urban and environmental data; (2) conversational multi-agent systems powered by LLMs and Retrieval-Augmented Generation (RAG) for user-centered fire intelligence; and (3) lightweight generative models optimized for edge devices, enabling on-site predictions in real time, even under limited connectivity. While promising, these approaches face critical challenges in multimodal data fusion, model interpretability, energy efficiency, and edge deployment. Overcoming these barriers is essential for realizing scalable, trustworthy, and sustainable AI systems for next-generation wildfire management and response.

References

Abdollahi, A., Pradhan, B., 2023. Explainable artificial intelligence (xai) for interpreting the contributing factors feed into the wildfire susceptibility prediction model. Science of the Total Environment 879, 163004.

Abdollahi, A., Yebra, M., 2025. Challenges and opportunities in remote sensing-based fuel load estimation for wildfire behavior and management: A comprehensive review. Remote Sensing 17, 415.

Andrianarivony, H.S., Akhloufi, M.A., 2024. Machine learning and deep learning for wildfire spread prediction: A review. Fire 7, 482.

Annane, B., Lakehal, A., Alti, A., 2024. Secured forest fire prediction using blockchain and cnn transformers, in: 2024 International Conference on Information and Communication Technologies for Disaster Management (ICT-DM), IEEE. pp. 1–7.

Bandi, A., Adapa, P.V.S.R., Kuchi, Y.E.V.P.K., 2023. The power of generative ai: A review of requirements, models, input–output formats, evaluation metrics, and challenges. Future Internet 15, 260.

Baptiste Filippi, J., Bosseur, F., Mari, C., Lac, C., Le Moigne, P., Cuenot, B., Veynante, D., Cariolle, D., Balbi, J.H., 2009. Coupled atmosphere-wildland fire modelling. Journal of Advances in Modeling Earth Systems 1.

Barbierato, E., Gatti, A., 2024. Toward green ai: A methodological survey of the scientific literature. IEEE Access 12, 23989–24013.

Bowman, D.M., Kolden, C.A., Abatzoglou, J.T., Johnston, F.H., van der Werf, G.R., Flannigan, M., 2020. Vegetation fires in the anthropocene. Nature Reviews Earth & Environment 1, 500–515.

Brown, T.B., et al., 2020. Language models are few-shot learners. NeurIPS .

Chen, D., Cheng, S., Hu, J., Kasoar, M., Arcucci, R., 2024. Explainable global wildfire prediction models using graph neural networks. arXiv preprint arXiv:2402.07152 .

Cheng, S., Guo, Y., Arcucci, R., 2023. A generative model for surrogates of spatial-temporal wildfire nowcasting. IEEE Transactions on Emerging Topics in Computational Intelligence 7, 1420–1430.

Deepa, N., Husain, S.O., Ezhil, G., Indhumathi, V., Revathi, R., 2024. An effective forest fire prediction based on contrastive vision transformer with pool former, in: 2024 International Conference on Integrated Intelligence and Communication Systems (ICIICS), IEEE. pp. 1–5.

Dhariwal, P., Nichol, A., 2021. Diffusion models beat gans on image synthesis. Advances in neural information processing systems 34, 8780–8794.

Diakite, A., Ng, L., Barton, J., Rigby, M., Williams, K., Barr, S., Zlatanova, S., 2022. Liveable city digital twin: a pilot project for the city of liverpool (nsw, australia). ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences 10, 45–52.

Dilo, A., Zlatanova, S., 2011. A data model for operational and situational information in emergency response: The dutch case. Applied Geomatics 3, 207–218.

Dinh, L., Sohl-Dickstein, J., Bengio, S., 2016. Density estimation using real nvp. arXiv preprint arXiv:1605.08803 .

Dinh, L., et al., 2017. Density estimation using real nvp, in: ICLR.

Dipierro, S., Valdinoci, E., Wheeler, G., Wheeler, V.M., 2024. A simple but effective bushfire model: analysis and real-time simulations. SIAM Journal on Applied Mathematics 84, 1504–1514.

Doerr, S.H., Santín, C., 2016. Global trends in wildfire and its impacts: perceptions versus realities in a changing world. Philosophical Transactions of the Royal Society B: Biological Sciences 371, 20150345.

Doshi-Velez, F., Kim, B., 2017. Towards a rigorous science of interpretable machine learning. arXiv preprint arXiv:1702.08608 .

Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., Dehghani, M., Minderer, M., Heigold, G., Gelly, S., et al., 2020. An image is worth 16x16 words: Transformers for image recognition at scale. arXiv preprint arXiv:2010.11929 .

EPA, 2025. California wildfires response. URL: `https://www.epa.gov/california-wildfires`. accessed: YYYY-MM-DD.

Falcão, G., Fernandes, A.M., Garcia, N., Aidos, H., Tomás, P., 2023. Stacking deep learning models for early detection of wildfire smoke plumes, in: 2023 31st European Signal Processing Conference (EUSIPCO), IEEE. pp. 1370–1374.

Finney, M.A., 1998. FARSITE, Fire Area Simulator–model development and evaluation. 4, US Department of Agriculture, Forest Service, Rocky Mountain Research Station.

Finney, M.A., Cohen, J.D., McAllister, S.S., Jolly, W.M., 2012. On the need for a theory of wildland fire spread. International journal of wildland fire 22, 25–36.

Fui-Hoon Nah, F., Zheng, R., Cai, J., Siau, K., Chen, L., 2023. Generative ai and chatgpt: Applications, challenges, and ai-human collaboration.

Gal, Y., Ghahramani, Z., 2016. Dropout as a bayesian approximation: Representing model uncertainty in deep learning, in: International Conference on Machine Learning (ICML), pp. 1050–1059.

Gazette, H., 2025. Death, destruction, and trauma of l.a. wildfires: Los angeles paradise fire. URL: `https://news.harvard.edu/gazette/story/2025/01/death-destruction-and-trauma-of-l-a-wildfires-los-angeles-paradise-fire/`. accessed: YYYY-MM-DD.

Ghali, R., Akhloufi, M.A., 2023. Deep learning approaches for wildland fires using satellite remote sensing data: Detection, mapping, and prediction. Fire 6, 192.

Ghali, R., Akhloufi, M.A., Jmal, M., Souidene Mseddi, W., Attia, R., 2021. Wildfire segmentation using deep vision transformers. Remote Sensing 13, 3527.

Ghali, R., Akhloufi, M.A., Mseddi, W.S., 2022. Deep learning and transformer approaches for uav-based wildfire detection and segmentation. Sensors 22, 1977.

Goodfellow, I.J., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., Bengio, Y., 2014. Generative adversarial nets. Advances in neural information processing systems 27.

Ho, J., Jain, A., Abbeel, P., 2020. Denoising diffusion probabilistic models. Advances in neural information processing systems 33, 6840–6851.

Hochreiter, S., Bengio, Y., Frasconi, P., Schmidhuber, J., 2001. Gradient flow in recurrent nets: the difficulty of learning long-term dependencies, in: A Field Guide to Dynamical Recurrent Neural Networks. IEEE Press, pp. 237–243.

Hu, Z., Ye, Y., Yang, Z., et al., 2024. Edge computing-based wildfire detection and optimization algorithm, in: 2024 7th International Conference on Advanced Algorithms and Control Engineering (ICAACE).

Jain, P., Coogan, S.C., Subramanian, S.G., Crowley, M., Taylor, S., Flannigan, M.D., 2020. A review of machine learning applications in wildfire science and management. Environmental Reviews 28, 478–505.

Johnston, F.H., Henderson, S.B., Chen, Y., Randerson, J.T., Marlier, M., DeFries, R.S., Kinney, P., Bowman, D.M., Brauer, M., 2012. Estimated global mortality attributable to smoke from landscape fires. Environmental health perspectives 120, 695–701.

Khanmohammadi, S., Arashpour, M., Golafshani, E.M., Cruz, M.G., Rajabifard, A., 2023. An artificial intelligence framework for predicting fire spread sustainability in semiarid shrublands. International journal of wildland fire 32, 636–649.

Khanmohammadi, S., Cruz, M.G., Perrakis, D.D., Alexander, M.E., Arashpour, M., 2024. Using automl and generative ai to predict the type of wildfire propagation in canadian conifer forests. Ecological Informatics 82, 102711.

Kingma, D.P., Dhariwal, P., 2018. Glow: Generative flow with invertible 1×1 convolutions, in: Advances in Neural Information Processing Systems.

Kingma, D.P., Welling, M., et al., 2013. Auto-encoding variational bayes.

Krapu, C., Borsuk, M., Calder, R., 2024. Deep autoregressive modeling for land use land cover. arXiv preprint arXiv:2401.01395 .

Kwon, B.C., Friedman, S., Xu, K., Lubitz, S.A., Philippakis, A., Batra, P., Ellinor, P.T., Ng, K., 2023. Latent space explorer: Visual analytics for multimodal latent space exploration. arXiv preprint arXiv:2312.00857 .

Lakshminarayanan, B., Pritzel, A., Blundell, C., 2017. Simple and scalable predictive uncertainty estimation using deep ensembles. Advances in Neural Information Processing Systems (NeurIPS) 30.

Lee, S.I., Koo, K., Lee, J.H., et al., 2024. Vision transformer models for mobile/edge devices: A survey. Multimedia Systems 30, 109. doi:10.1007/s00530-024-01312-0.

Li, B.S., Rad, R., 2024. Wildfire spread prediction in north america using satellite imagery and vision transformer, in: 2024 IEEE Conference on Artificial Intelligence (CAI), IEEE. pp. 1536–1541.

Li, J., Hong, D., Gao, L., Yao, J., Zheng, K., Zhang, B., Chanussot, J., 2022. Deep learning in multimodal remote sensing data fusion: A comprehensive review. International Journal of Applied Earth Observation and Geoinformation 112, 102926.

Li, X., Luo, S., He, Y., Liu, Y., 2020. Misgan: Learning from incomplete data with generative adversarial networks. ICLR .

Li, X., Xu, H., Tupayachi, J., Omitaomu, O., Wang, X., 2024a. Empowering cognitive digital twins with generative foundation models: Developing a low-carbon integrated freight transportation system. arXiv preprint arXiv:2410.18089 .

Li, Y., Li, K., Guohui, L., Ji, C., Wang, L., Zuo, D., Guo, Q., Zhang, F., Wang, M., Lin, D., et al., 2024b. Sim2real-fire: A multi-modal simulation dataset for forecast and backtracking of real-world forest fire. Advances in Neural Information Processing Systems 37, 1428–1442.

Limber, R., Hargrove, W.W., Hoffman, F.M., Kumar, J., 2024. Forecast of wildfire potential across california usa using a transformer, in: 2024 IEEE International Conference on Big Data (BigData), IEEE. pp. 4342–4350.

Liu, Y., Jun, E., Li, Q., Heer, J., 2019. Latent space cartography: Visual analysis of vector space embeddings, in: Computer graphics forum, Wiley Online Library. pp. 67–78.

Ma, Z., Mei, G., Xu, N., 2024. Generative deep learning for data generation in natural hazard analysis: motivations, advances, challenges, and opportunities. Artificial Intelligence Review 57, 160.

Mahdi, A.S., Mahmood, S.A., 2022. An edge computing environment for early wildfire detection. Annals of Emerging Technologies in Computing (AETiC) 6. doi:10.33166/AETiC.2022.03.005.

Mambile, C., Kaijage, S., Leo, J., 2024. Application of deep learning in forest fire prediction: A systematic review. IEEE Access .

Manduchi, L., Pandey, K., Meister, C., Bamler, R., Cotterell, R., Däubener, S., Fellenz, S., Fischer, A., Gärtner, T., Kirchler, M., et al., 2024. On the challenges and opportunities in generative ai. arXiv preprint arXiv:2403.00025 .

Mell, W., Jenkins, M.A., Gould, J., Cheney, P., 2007. A physics-based approach to modelling grassland fires. International Journal of Wildland Fire 16, 1–22.

Miller, C., Hilton, J., Sullivan, A., Prakash, M., 2015. Spark–a bushfire spread prediction tool, in: International Symposium on Environmental Software Systems, Springer. pp. 262–271.

Mohammad, A., Gullapalli, O.S., Vasavi, S., Jayanthi, S., 2022. Updating of gis maps with change detection of buildings using deep learning techniques, in: 2022 International Conference on Futuristic Technologies (INCOFT), IEEE. pp. 1–6.

Moinuddin, K., Tirado Cortes, C., Hassan, A., Accary, G., Wu, F., 2024. Simulation of extreme fire event scenarios using fully physical models and visualisation systems, in: Climate Disaster Preparedness: Reimagining Extreme Events through Art and Technology. Springer Nature Switzerland Cham, pp. 49–63.

Myers, D., Mohawesh, R., Chellaboina, V.I., Sathvik, A.L., Venkatesh, P., Ho, Y.H., Henshaw, H., Alhawawreh, M., Berdik, D., Jararweh, Y., 2024. Foundation and large language models: fundamentals, challenges, opportunities, and social impacts. Cluster Computing 27, 1–26.

Niloofar, P., Lazarova-Molnar, S., Omitaomu, F., Xu, H., Li, X., 2023. A general framework for human-in-the-loop cognitive digital twins, in: 2023 Winter Simulation Conference (WSC), IEEE. pp. 3202–3213.

Noble, I., Gill, A., Bary, G., 1980. Mcarthur's fire-danger meters expressed as equations. Australian journal of ecology 5, 201–203.

Papamakarios, G., Nalisnick, E., Rezende, D.J., Mohamed, S., Lakshminarayanan, B., 2021. Normalizing flows for probabilistic modeling and inference. Journal of Machine Learning Research 22, 1–64.

Pugnet, L., Chong, D., Duff, T., Tolhurst, K., 2013. Wildland–urban interface (wui) fire modelling using phoenix rapidfire: A case study in cavaillon, france, in: Proceedings of the 20th International Congress on Modelling and Simulation, Adelaide, Australia, pp. 1–6.

Radford, A., Kim, J.W., Hallacy, C., Ramesh, A., Goh, G., Agarwal, S., Sastry, G., Askell, A., Mishkin, P., Clark, J., et al., 2021. Learning transferable visual models from natural language supervision, in: International conference on machine learning, PmLR. pp. 8748–8763.

Radke, D., Hessler, A., Ellsworth, D., 2019. Firecast: Leveraging deep learning to predict wildfire spread., in: IJCAI, pp. 4575–4581.

Richards, G.D., 1995. A general mathematical framework for modeling two-dimensional wildland fire spread. International Journal of Wildland

Fire 5, 63–72.

Rombach, R., Blattmann, A., Lorenz, D., Esser, P., Ommer, B., 2022. High-resolution image synthesis with latent diffusion models, in: Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, pp. 10684–10695.

Rothermel, R.C., 1972. A mathematical model for predicting fire spread in wildland fuels. volume 115. Intermountain Forest & Range Experiment Station, Forest Service, US . . . .

Rudin, C., 2019. Stop explaining black box machine learning models for high-stakes decisions and use interpretable models instead. Nature Machine Intelligence 1, 206–215.

Saharia, C., Ho, J., Chan, W., Salimans, T., Fleet, D.J., Norouzi, M., 2022. Image super-resolution via iterative refinement. IEEE transactions on pattern analysis and machine intelligence 45, 4713–4726.

Salehi, S., Schmeink, A., 2023. Data-centric green artificial intelligence: A survey. IEEE Transactions on Artificial Intelligence 5, 1973–1989.

Shadrin, D., Illarionova, S., Gubanov, F., Evteeva, K., Mironenko, M., Levchunets, I., Belousov, R., Burnaev, E., 2024. Wildfire spreading prediction using multimodal data and deep neural network approach. Scientific Reports 14, 2606.

Shen, H., Li, X., Cheng, Q., Zeng, C., Yang, G., Li, H., Zhang, L., 2015. Missing information reconstruction of remote sensing data: A technical review. IEEE Geoscience and Remote Sensing Magazine 3, 61–85.

Singh, H., Ang, L.M., Paudyal, D., Acuna, M., Srivastava, P.K., Srivastava, S.K., 2025. A comprehensive review of empirical and dynamic wildfire simulators and machine learning techniques used for the prediction of wildfire in australia. Technology, Knowledge and Learning , 1–34.

Song, J., Li, J., Chen, H., Wu, J., 2021. Mapgen-gan: A fast translator for remote sensing image to map via unsupervised adversarial learning. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 14, 2341–2357.

Spiller, D., Thangavel, K., Sasidharan, S.T., et al., 2022. Wildfire segmentation analysis from edge computing for on-board real-time alerts using hyperspectral imagery, in: 2022 IEEE International Conference on Metrology for eXtended Reality, Artificial Intelligence and Neural Engineering (MetroXRAINE).

Sullivan, A.L., 2009a. Wildland surface fire spread modelling, 1990–2007. 1: Physical and quasi-physical models. International Journal of Wildland Fire 18, 349–368.

Sullivan, A.L., 2009b. Wildland surface fire spread modelling, 1990–2007. 2: Empirical and quasi-empirical models. International Journal of Wildland Fire 18, 369–386.

Sullivan, A.L., 2009c. Wildland surface fire spread modelling, 1990–2007. 3: Simulation and mathematical analogue models. International Journal of Wildland Fire 18, 387–403.

Sullivan, A.L., 2009d. Wildland surface fire spread modelling, 1990–2007. 3: Simulation and mathematical analogue models. International Journal of Wildland Fire 18, 387–403.

Sun, Y., Jang, E., Ma, F., Wang, T., 2024. Generative ai in the wild: prospects, challenges, and strategies, in: Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems, pp. 1–16.

Taiwo, R., Yussif, A.M., Zayed, T., 2025. Making waves: Generative artificial intelligence in water distribution networks: Opportunities and challenges. Water Research X 28, 100316.

Tay, Y., Dehghani, M., Bahri, D., Metzler, D., 2022. Efficient transformers: A survey. ACM Computing Surveys 55, 1–28.

Tupayachi, J., Xu, H., Omitaomu, O.A., Camur, M.C., Sharmin, A., Li, X., 2024. Towards next-generation urban decision support systems through ai-powered construction of scientific ontology using large language models—a case in optimizing intermodal freight transportation. Smart Cities 7, 2392–2421.

Urbanski, S., 2014. Wildland fire emissions, carbon, and climate: Emission factors. Forest Ecology and Management 317, 51–60.

Van Den Oord, A., Dieleman, S., Zen, H., Simonyan, K., Vinyals, O., Graves, A., Kalchbrenner, N., Senior, A., Kavukcuoglu, K., et al., 2016. Wavenet: A generative model for raw audio. arXiv preprint arXiv:1609.03499 12.

Vargas, J.A.S., 2025. Development of a Wildfire Risk Prediction System based on Deep Learning Methods and Remote Sensing. Ph.D. thesis. Institute for Geoinformatics.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A.N., Kaiser, Ł., Polosukhin, I., 2017. Attention is all you need. Advances in neural information processing systems 30.

Wang, F., Tian, D., Lowe, L., Kalin, L., Lehrter, J., 2021. Deep learning for daily precipitation and temperature downscaling. Water Resources Research 57, e2020WR029308.

Wang, Z., Zlatanova, S., 2019. Safe route determination for first responders in the presence of moving obstacles. IEEE transactions on intelligent transportation systems 21, 1044–1053.

Wang, Z., Zlatanova, S., Moreno, A., Van Oosterom, P., Toro, C., 2014. A data model for route planning in the case of forest fires. Computers & Geosciences 68, 1–10.

Weil, C., Bibri, S.E., Longchamp, R., Golay, F., Alahi, A., 2023. Urban digital twin challenges: A systematic review and perspectives for sustainable smart cities. Sustainable Cities and Society 99, 104862.

Xie, Y., Jiang, B., Mallick, T., Bergerson, J.D., Hutchison, J.K., Verner, D.R., Branham, J., Alexander, M.R., Ross, R.B., Feng, Y., Levy, L.A., Su, W., Taylor, C.J., 2025. Wildfiregpt: Tailored large language model for wildfire analysis. arXiv preprint arXiv:2402.07877 .

Xu, H., Berres, A., Shao, Y., Wang, C.R., New, J.R., Omitaomu, O.A., 2023a. Toward a smart metaverse city: Immersive realism and 3d visualization of digital twin cities. Advances in Scalable and Intelligent Geospatial Analytics , 245–257.

Xu, H., Berres, A., Yoginath, S.B., Sorensen, H., Nugent, P.J., Severino, J., Tennille, S.A., Moore, A., Jones, W., Sanyal, J., 2023b. Smart mobility in the cloud: Enabling real-time situational awareness and cyber-physical control through a digital twin for traffic. IEEE Transactions on Intelligent Transportation Systems 24, 3145–3156.

Xu, H., Boyaci, A., Lian, J., Wilson, A., 2024a. Explainable ai for multivariate time series pattern exploration: Latent space visual analytics with temporal fusion transformer and variational autoencoders in power grid event diagnosis. arXiv e-prints , arXiv–2412.

Xu, H., Li, X., Tupayachi, J., Lian, J.J., Omitaomu, O.A., 2024b. Automating bibliometric analysis with sentence transformers and retrieval-augmented generation (rag): A pilot study in semantic and contextual search for customized literature characterization for high-impact urban research, in: Proceedings of the 2nd ACM SIGSPATIAL International Workshop on Advances in Urban-AI, pp. 43–49.

Xu, H., Omitaomu, F., Sabri, S., Zlatanova, S., Li, X., Song, Y., 2024c. Leveraging generative ai for urban digital twins: a scoping review on the autonomous generation of urban data, scenarios, designs, and 3d city models for smart city advancement. Urban Informatics 3, 29.

Xu, H., Yuan, J., Berres, A., et al., 2024d. A mobile edge computing framework for traffic optimization at urban intersections through cyber-physical integration. IEEE Transactions on Intelligent Vehicles 9. doi:10.1109/TIV.2023.3332256.

Xu, H., Yuan, J., Zhou, A., Xu, G., Li, W., Ban, X., Ye, X., 2024e. Genai-powered multi-agent paradigm for smart urban mobility: Opportunities and challenges for integrating large language models (llms) and retrieval-augmented generation (rag) with intelligent transportation systems. arXiv preprint arXiv:2409.00494 .

Xu, Z., Li, J., Cheng, S., Rui, X., Zhao, Y., He, H., Xu, L., 2024f. Wildfire risk prediction: A review. arXiv preprint arXiv:2405.01607 .

Yan, L., Greiff, S., Teuber, Z., Gašević, D., 2024. Promises and challenges of generative artificial intelligence for human learning. Nature Human Behaviour 8, 1839–1850.

Yang, W., Zhang, X., Tian, Y., Wang, W., Xue, J.H., Liao, Q., 2019. Deep learning for single image super-resolution: A brief review. IEEE Transactions on Multimedia 21, 3106–3121.

Zheng, X., Lu, J., Kiritsis, D., 2022. The emergence of cognitive digital twin: vision, challenges and opportunities. International Journal of Production Research 60, 7610–7632.

Zhou, J., Chen, Y., Hong, Z., Chen, W., Yu, Y., Zhang, T., Wang, H., Zhang, C., Zheng, Z., 2024. Training and serving system of foundation models: A comprehensive survey. IEEE Open Journal of the Computer Society .