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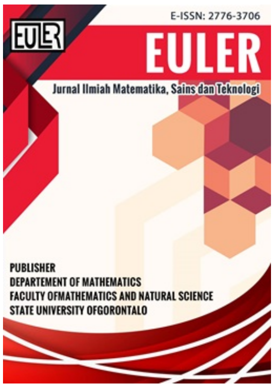

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Review Article

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Systematic Literature Review on the Application of Mathematics, Statistics, and Computer Science in Wildfire Analysis

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ABSTRACT. *Wildfires pose a significant threat to ecosystems, human settlements, and air quality, making accurate prediction and analysis crucial for disaster mitigation. Traditional statistical methods often struggle with the vast and complex nature of wildfire data, necessitating advanced mathematical, statistical, and computational approaches. This study presents a systematic literature review of wildfire analysis techniques, focusing on trends from 2000 to 2025. By analyzing 6,498 articles using the PRISMA framework, we identify the most widely applied methods, such as correlation, regression, classification, clustering, and artificial neural networks, while highlighting underutilized yet promising techniques such as copula, fuzzy inference, image recognition, quantile mapping, and empirical orthogonal function (EOF). The findings reveal an increasing shift toward interdisciplinary, data-driven approaches, with a significant increase in high-impact publications over the last decade. We emphasize the need for further exploration of advanced methodologies to enhance wildfire prediction models and improve decision-making in fire-prone regions. This review bridges computational innovations with environmental challenges, this study provides a roadmap for future research in wildfire analysis and management.*

1. Introduction

Wildfires can be analyzed using various types of data, such as burned area data and the number of hotspot occurrences. Currently, hotspots are the most effective indicator for monitoring wildfires and land fires over large areas quickly. Satellite technology enables near real-time wildfire and land fire monitoring. Research on hotspots is closely related to other influencing factors. For instance, to confirm that a detected hotspot is indeed a wildfire, confidence level analysis is required based on aspects such as temperature, clouds, fog, and water consistency [1]. This approach ensures that the data used for fire detection is accurate and not misinterpreted due to environmental noise. Additionally, hotspot data can be combined with climate data such as temperature, precipitation, visibility, and even El Niño. Integrating these variables allows researchers to identify patterns and correlations that may not be evident when variables are analyzed separately. This combination helps establish relationships between climate indicators and hotspots [2, 3]. Understanding these relationships is crucial because they offer predictive insights. These relationships can provide valuable information for early detection of wildfire and land fire events [4]. Early detection, in turn, supports more effective fire prevention and mitigation strategies.

Wildfire data provides spatial and temporal information with large size and dimensions. Therefore, it requires specific processing methods to extract valuable insights that can aid decision-making [5]. The complexity and volume of such data often surpass the capabilities of traditional analysis techniques, making it challenging to derive timely and accurate conclusions. Classical statistical analysis has limitations in handling extensive datasets such as hotspot data. These methods typically rely on assumptions that may not hold for dynamic, high-dimensional wildfire data. Hence, data mining tools offer an alternative for extracting high-level information from large data sets [6]. By leveraging computational power and pattern recognition capabilities, data mining techniques can uncover trends, correlations, and anomalies that might be missed by conventional methods.

Several data mining methods, or more broadly, computer science techniques, can be used for wildfire data analysis, including decision trees, random forests, logistic regression [7], the DBSCAN algorithm [8], supervised machine learning [9], and neural networks [10–12]. These methods are particularly useful for handling large datasets and uncovering hidden patterns or anomalies related to wildfire occurrences. Besides computer science methods, mathematical and statistical techniques can also be applied to wildfire analysis, such as regression methods [13, 14], principal component analysis [15], empirical orthogonal function using singular value decomposition [16], wavelet transformation [17], stochastic average gradient descent [18], copula[19], and auto-regressive models [20]. These approaches allow researchers to model complex relationships among variables, reduce dimensionality in large datasets, and identify key contributing factors in wildfire events with greater accuracy.

The application of mathematics, statistics, and computer science methods has rapidly developed in recent years in wildfire data analysis. This article presents a systematic literature re-

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view on wildfire analysis utilizing mathematical, statistical, and computer science methods from 2000 to 2025. In addition to providing a comprehensive summary of the topics and methodologies applied over the past two decades, this review offers a unique contribution by identifying and emphasizing underutilized yet promising techniques, such as copula, fuzzy inference, image recognition, quantile mapping, and empirical orthogonal function (EOF). Furthermore, the study highlights the growing trend toward interdisciplinary, data-driven approaches that combine environmental science with computational modeling. By mapping out both widely used and emerging methods, this review serves as a roadmap for future research, helping scholars target methodological gaps and explore innovative strategies in wildfire prediction and management.

2. Methods

The method used in this systematic literature review is the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA), introduced by Moher et al. [21]. This method provides a structured and transparent approach that enhances the reproducibility and reliability of review studies. PRISMA is one of the best methods for conducting systematic reviews and meta-analyses correctly, as well as for helping researchers structure their review like a roadmap [22]. Its standardized framework ensures that essential components such as inclusion criteria, data extraction, and synthesis are consistently applied. PRISMA is also the most used method in systematic literature reviews [23, 24], reflecting its wide acceptance and effectiveness across various scientific disciplines.

A systematic literature review serves as a valuable reference source. It provides a comprehensive overview of existing research, allowing for the identification of trends, gaps, and future research directions in a given field. Researchers must systematically summarize and analyse scientific literature relevant to a defined objective so that other researchers can utilize the findings [25]. This systematic approach ensures transparency, minimizes bias, and enhances the credibility of the conclusions drawn. Systematic reviews play a crucial role in solving problems by explaining, synthesizing, and assessing quantitative or qualitative evidence [26]. As such, they are particularly useful in fields where diverse methodologies and data sources need to be integrated. The PRISMA procedure in this study follows the steps outlined below.

2.1. Research Questions

To focus the analysis process, the first step is to formulate the research questions related to the information being sought. The research questions for this article, which examines wildfire analysis using mathematical, statistical, and computer science methods, are as follows:

- How has the development progressed over the years?
- What is the distribution of journal rankings?
- Which journals most frequently publish these studies?
- What are the most used methods, and which methods are still underutilized?

After gathering this information, recent articles that apply underutilized methods will be reviewed and analysed.

2.2. Meta-Data Search Strategy

At this stage, a search for scientific articles related to wildfire research was conducted in scientific journals indexed in Scopus and Google Scholar. The primary source used was Scopus, while Google Scholar served as a complementary source. The keywords used for article searches were HOTSPOT, FOREST FIRE, BURNED AREA, or WILDFIRE, with additional search criteria to exclude the keywords BIOLOGY and Wi-Fi. The search was further restricted to the fields of environmental sciences and earth and planetary sciences. This approach ensured that the search results focused on wildfire-related studies while eliminating irrelevant topics, such as hotspots in Wi-Fi networks or species distribution in biology. To further refine the meta-data search, additional keywords related to mathematical, statistical, and computer science methods were included, such as correlation, regression, classification, neural network, machine learning, artificial intelligence, clustering, downscaling, Monte Carlo, genetic algorithm, support vector machine, random forest, principal component, wavelet, empirical orthogonal function (EOF), Fourier, fuzzy inference, linear programming, k-means, quantile mapping, reinforcement learning, supervised learning, unsupervised learning, copula, and image recognition. The selected articles were limited to those published until March 13, 2025. The article search began with Scopus-indexed articles using the search feature on scopus.com with the following query:

```
TITLE-ABS-KEY ( hotspot OR "forest fire" OR
"burned area" OR "wildfire" ) AND ( TITLE-ABS-KEY
( correlation OR regression OR classification
OR "neural network" OR "machine learning"
OR "artificial intelligence" OR clustering
OR downscaling OR "monte carlo" OR "genetic
algorithm" OR "support vector machine" OR "random
forest" OR "principal component" OR wavelet OR
eof OR fourier OR "fuzzy inference" OR "linear
programming" OR k-means OR "quantile mapping" OR
"reinforcement learning" OR "supervised learning"
OR "unsupervised learning" OR copula OR blockchain
OR "image recognition" ) ) AND NOT ( "biology" OR
"Wi-Fi" ) AND ( LIMIT-TO ( SUBJAREA , "ENVI" ) OR
LIMIT-TO ( SUBJAREA , "EART" ) ).
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Based on this search, 7,740 articles were retrieved from Scopus. After classification, several methods were identified as being underutilized and/or Scopus-indexed, including copula, fuzzy inference, image recognition, quantile mapping, and empirical orthogonal function. Therefore, the article search process was continued using Publish or Perish (PoP) to retrieve additional Google Scholar-indexed articles for inclusion in the systematic literature review of each underutilized method.

2.3. Meta-Data Screening

The meta-data screening process was conducted based on eligibility criteria, which were used to select relevant articles. These eligibility criteria are also known as inclusion criteria, while the criteria for excluding articles are referred to as exclusion criteria. The inclusion criteria used in this study are presented in Table 1.

Based on the criteria in Table 1, articles that were published before 2000, written in languages other than Indonesian or En-

Table 1. Inclusion criteria

Criteria	Inclusion
Time Period	1 Jan 2000 – 3 Mar 2025
Language	Indonesian or English
Document Type	Journal articles and conference papers
Topic	Wildfire analysis
Methods	Utilizes the methods mentioned in the meta-data search strategy

glish, or had document types other than journal articles and conference papers—such as books, book chapters, theses, dissertations, reports, or review papers—were eliminated. The screening process was conducted by reviewing the title, abstract, and keywords (both author keywords and index keywords) in the article meta-data. After applying the exclusion criteria, 1,242 articles were found to be ineligible, leaving a total of 6,498 articles for further analysis.

2.4. Data Extraction and Analysis

From the 6,498 articles obtained, key information will be extracted and summarized to address the research questions in this systematic literature review. Based on the required information, the articles will be analysed according to several classifications and criteria that align with the research objectives using Ms. Excel and `Bibliometrix` package in R. The data extraction process is designed to classify, analyse, and synthesize articles that meet the predefined criteria. Based on the analysis of the extracted data, relevant recommendations can be formulated. The classification criteria include:

- Year of publication
- Publication source and ranking
- Author information
- Methods applied

After classification and review, the 6,498 articles consist of 5,856 international journal articles and 642 conference papers published between 2000 and 2025. Among these articles, the latest studies related to applied methods will be synthesized. Due to the structured nature of the PRISMA methodology, only the most relevant and appropriate articles are selected for this study.

3. Results and Discussion

The findings from the analysis and synthesis of the relevant articles are presented in this section. Based on the systematic literature review, various mathematical, statistical, and computational methods that have been applied in wildfire research were identified. Therefore, studies that meet the criteria are summarized and classified based on the year of publication, publication source and ranking, author information, and methods applied.

To better understand the landscape of research in wildfire analysis using mathematical, statistical, and computer science methods, it is important to examine the overall trends in publication output. By analyzing the quantity, collaboration patterns, and citation metrics of the reviewed articles, we can gain insights into the growth, impact, and scholarly engagement within this field. Figure 1 presents a comprehensive overview of the documents analyzed in this review, highlighting key bibliometric indicators that reflect the evolution and significance of research efforts over the past two decades.

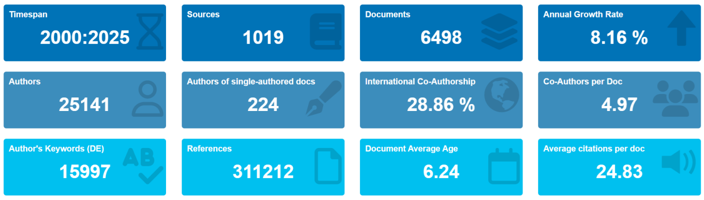


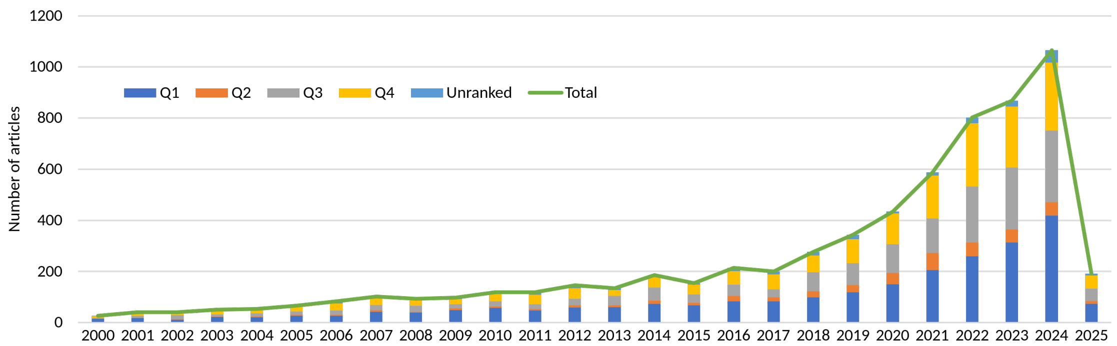
Figure 1. Documents' overview

Figure 1 shows that the systematic literature review results provide a comprehensive overview of research trends from 2000 to 2025. A total of 6,498 documents from 1,019 sources have been analysed, showing an annual growth rate of 8.16%, indicating a steady increase in research output. The study involves contributions from 25,141 authors, with a relatively small proportion (224) of single-authored works, highlighting a strong collaborative nature. International co-authorship accounts for 28.86% of publications, and the average number of co-authors per document is 4.97, further emphasizing global research collaboration. The dataset contains 15,997 distinct keywords, reflecting diverse research themes, and 311,212 references, underscoring the depth of scholarly engagement. The average age of documents is 6.24 years, suggesting a balanced mix of recent and foundational studies. Each document receives an average of 24.83 citations, indicating a significant impact within the academic community.

3.1. Articles Based on Year of Publication

This subsection presents the temporal distribution of wildfire-related research articles published between 2000 and 2025. The analysis aims to identify publication trends over time and to assess the development of scientific interest in the application of mathematics, statistics, and computer science in wildfire analysis. The data were obtained through bibliometric analysis of 6,498 selected articles using the Bibliometrix package in R. The annual distribution of publications is visualized in Figure 2.

Figure 2 illustrate the publication trends over time, highlighting a significant increase in research output, particularly in the last decade. The bar chart is segmented by different colours representing the SJR (SCImago Journal Rank) quantile rankings, indicating the distribution of publications across various journal quality tiers. The overall trend shows steady growth from 2000, with a sharp increase after 2010, peaking in 2022–2024. This surge suggests a growing academic focus on wildfire-related challenges and the development of computational tools to address them. The decline in 2025 is due to data being available only until March 3, meaning the full year's research output has yet to be captured. The green line, representing cumulative growth, maintains a consistent upward trajectory, confirming the expanding research interest in the field. Over time, the increasing presence of higher-ranked journals suggests a shift toward publishing in more reputable sources, reflecting the maturation and growing impact of research within this domain.



	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
Unranked	2	0	1	1	2	4	9	4	7	5	0	10	12	6	5	5	12	11	14	17	7	13	22	23	48	8
Q4	7	15	10	18	14	19	27	29	21	20	35	37	41	23	44	38	53	59	65	94	121	168	247	239	266	51
Q3	3	8	16	8	13	13	17	20	24	15	21	19	25	37	51	33	45	31	74	85	112	135	220	242	280	48
Q2	0	0	3	2	3	4	4	7	3	8	5	5	9	8	12	10	20	15	24	29	44	67	53	50	52	11
Q1	15	18	11	22	21	27	27	42	39	49	58	48	59	60	74	68	84	84	99	119	150	205	260	314	419	74
Total	27	41	41	51	53	67	84	102	94	97	119	119	146	134	186	154	214	200	276	344	434	588	802	868	1065	192

Figure 2. Trends in research publications (2000–2025) categorized by SJR quantile rankings. The bar segments represent the distribution of publications across different journal quality tiers, while the green line indicates cumulative growth

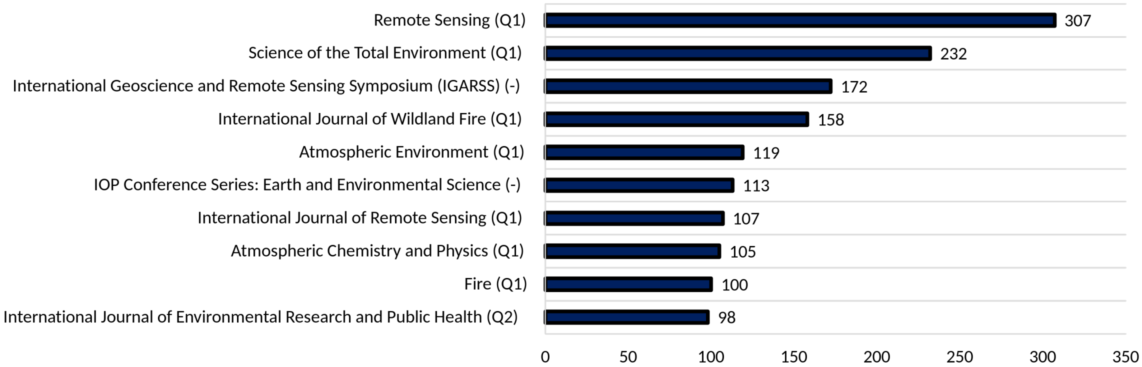


Figure 3. Top 10 journals publishing articles related to forest fire analysis using mathematics, statistics, and computer science techniques

3.2. Sources of Articles

This subsection analyzes the distribution of articles based on their publication sources to identify which journals have most actively contributed to the discourse on wildfire analysis. The goal is to determine the quality and focus of journals that serve as primary platforms for disseminating research in this field. The analysis also includes classification based on SCImago Journal Rank (SJR) to reflect the scholarly impact of each source. Cumulatively, between 2000 and 2025, the number of articles published in Q1, Q2, Q3, and Q4 journals will have percentage ratios of 37.6%, 6.9%, 24.5%, and 27.1%, respectively, with the remaining 3.8% being in unranked journals. The publication sources and their ranking distributions are summarized in Figure 3.

Figure 3 reveals that Remote Sensing (Q1) is the most dominant journal, publishing 307 articles in this domain. This is followed by Science of the Total Environment (Q1) and International Journal of Wildland Fire (Q1), indicating that top-tier journals in environmental and geospatial sciences are key platforms for wildfire research. Other notable Q1 journals include Atmospheric Environment, Atmospheric Chemistry and Physics, and Remote Sensing of Environment. Meanwhile, interdisciplinary journals like Journal of Cleaner Production and ISPRS International Journal of Geo-Information also play significant roles. The diversity in journal categories, from environmental engineering to geoinformatics, reflects the interdisciplinary nature of wildfire analysis, which blends environmental science with advanced computational methods.

3.3. Most Relevant Authors and Lotka's Law

This subsection explores the productivity and impact of authors in wildfire research using bibliometric indicators. It aims to identify key contributors, examine trends in scientific output over time, and evaluate how author productivity aligns with Lotka's Law, i.e., a principle that describes the distribution of scientific productivity among researchers. The analysis is based on publication frequency, total citations per year, and global author collaboration. The productivity and citation impact of authors are visualized in Figure 4, while country-level scientific output and the distribution of author productivity according to Lotka's Law are presented in Figure 5 and Figure 6, respectively.

Figure 4 highlights author productivity and citation impact over time in a bubble chart. Researchers like Bergeron, Chuvieco, And Flannigan have consistently published, while others, such as Liu and Fernandes, saw peak productivity in recent years. High impact works include Chuvieco (2010, TCpY = 25.75), De La Riva (2014, TCpY = 39.25), and Liu (2020, TCpY = 54), indicating their strong influence. Recent publications (2023–2025) generally have lower citations, likely due to limited exposure. While some authors, Fernandes (2018, TCpY = 38.37), and Quan (2018, TCpY = 16.25), have seen significant past recognition, newer

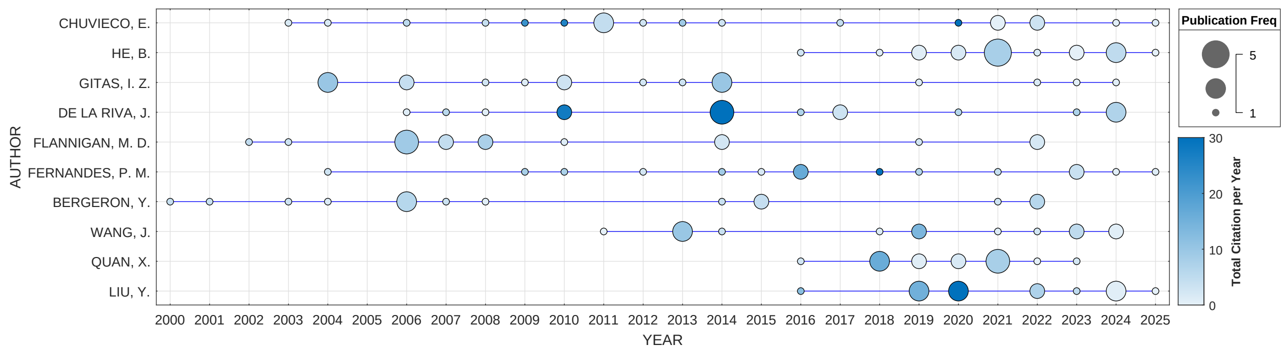


Figure 4. Authors' production over time

works need time to gain traction, suggesting their full impact is yet to be realized.

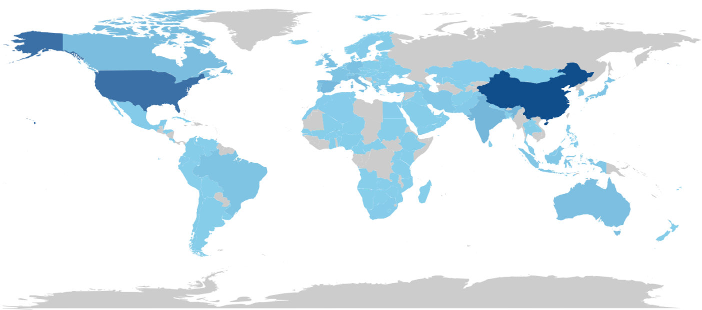


Figure 5. Countries' scientific production

Figure 5 presents the scientific production of various countries, measured by the frequency of their contributions. China (8,718) and the USA (6,235) dominate global research output, reflecting their robust scientific infrastructure and investment. India (1,498), Spain (1,256), Canada (1,108), and Italy (1,100) also exhibit significant contributions, indicating strong research engagement. Other notable contributors include Australia, Germany, the UK, Brazil, France, and Portugal. Emerging research nations like Indonesia, Malaysia, and Iran are increasing their presence, while African and South American countries, though contributing at lower frequencies, are actively engaging in scientific discourse.

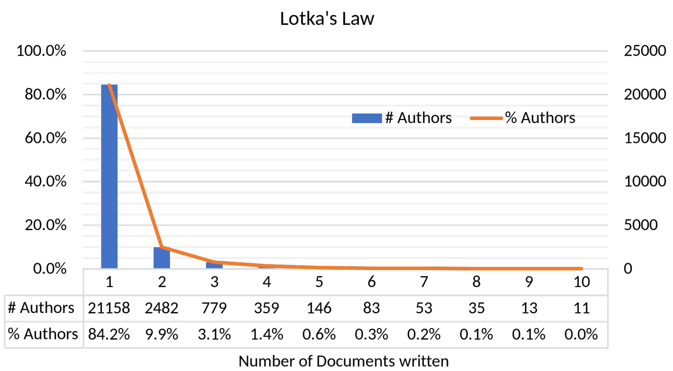


Figure 6. Countries' scientific production

Figure 6 represents Lotka's Law, which describes the distribution of scientific productivity among authors. It shows that most authors publish only one document (84.2%), while the number of authors decreases as the number of documents written increases. Specifically, only 9.9% of authors publish two documents, 3.1% publish three, and so on, with very few authors producing more than five publications.

The analysis of author productivity and scientific contributions reveals significant patterns in the development of wildfire research. A relatively small group of highly productive authors has played a pivotal role in advancing the field through consistent output and high citation impact, such as Liu, Chuvieco, Bergeron, and Flannigan. Their contributions not only reflect individual expertise but also serve as references that shape subsequent research directions. Meanwhile, the majority of authors contribute only one publication, a trend that aligns with Lotka's Law and highlights the typical distribution of scientific output, where a few prolific scholars dominate. From a geographical perspective, the dominance of countries like China and the USA underscores their investment in research infrastructure and climate-related challenges. However, the growing contributions from emerging research hubs such as Indonesia and Malaysia suggest an encouraging expansion of global participation in wildfire analysis. This increase in diversity enriches the field by bringing in varied perspectives, data sources, and methodological innovations. The overall findings emphasize the importance of fostering international collaboration and supporting emerging researchers to ensure sustainable knowledge growth and innovation in wildfire science.

3.4. *Classification of Articles by Method*

This subsection categorizes the 6,498 reviewed articles based on the analytical methods they applied, focusing on mathematical, statistical, and computer science techniques. The classification process aims to identify dominant methodological trends and highlight underutilized techniques that offer potential for future development. The methods were extracted from the metadata (titles, abstracts, and keywords) and categorized based on their frequency and type of approach. The distribution of articles by method is presented in Figure 7.

Statistical analysis such as correlation [27, 28] and regression [14, 29] are the most frequently used techniques with a percentage reaching 41.58%. Followed by several machine learning techniques such as classification [30, 31], clustering [32, 33], and artificial neural networks [34, 35]. These five methods are the most used techniques to analyse forest fires. Based on Figure 7,

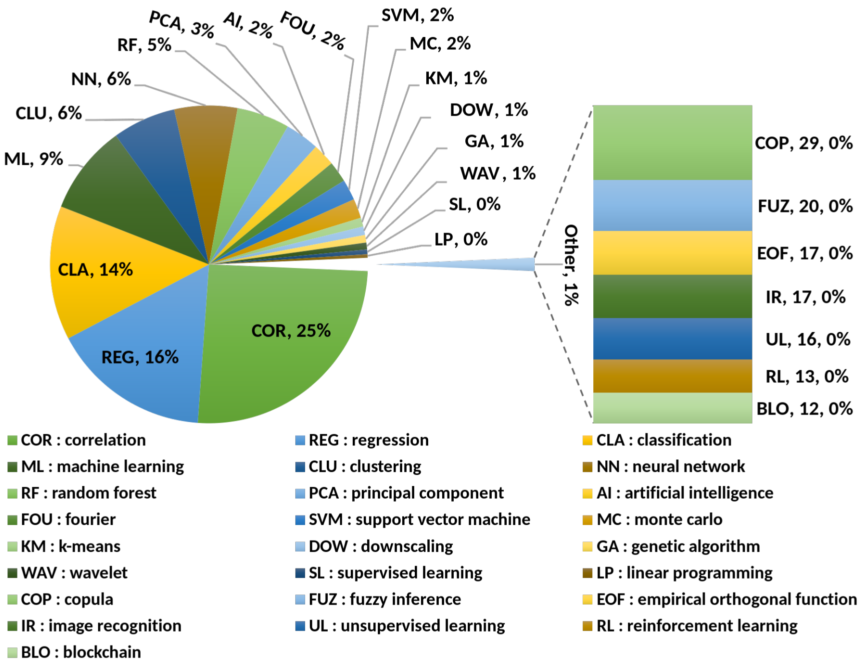


Figure 7. Classification of articles based on the mathematical, statistical, and computer science techniques used

the terms supervised, unsupervised, and reinforcement learning are rarely used in the title, abstract, and keywords. The author prefers to use the terms of the techniques used such as clustering and classification rather than using the type of learning used. In addition, some techniques are still rarely used and can be further developed such as copula, fuzzy inference, image recognition, quantile mapping, and empirical orthogonal function. Below is a discussion of several recent articles related to methods that are still rarely used in forest fire analysis.

3.4.1. Copula

Copula is defined as a function that links the multivariate distribution F_X with the univariate marginal distribution $F_{X_i}(x_i)$ [36]. The copula function represents the dependency between variables, which is an essential step in linking climate information with forest fire occurrences [37]. Several studies use copula to link information, such as precipitation-ENSO-hotspots [19, 38], compound drought-hot events [39], and hydrometeorological elements-wildfire [40]. In another study, the joint distribution of fire duration (in days) and burned area (in hectares) is modelled using bivariate copula [41]. Moreover, copula regression can also be used to predict the quantity of hotspots based on their relationship with climate indicators [42].

3.4.2. Fuzzy Inference

The classification method known as the Adaptive Neuro-Fuzzy Inference System (ANFIS), with its nonlinear modelling capability, has been used to develop classification models for predicting spatial forest fire vulnerability [43]. In Indonesia, ANFIS is applied to create a classification model for predicting hotspot occurrences in Central Kalimantan, showing that the ANFIS algorithm can effectively classify hotspots in the region, achieving a very low error rate of 0.0093676 [44].

3.4.3. Image Recognition

In 2015, Lum et al. [45] investigated unmanned aerial systems (UAS) for automated forest fire detection using low-cost sensors and image processing techniques. Their system detected fire-related features such as fire lines and burned areas while accounting for environmental occlusions like smoke and shadows. The image recognition algorithm enabled autonomous identification and classification of fires. Once detected, fires were analyzed through simulations incorporating vegetation, weather, and terrain factors [45].

3.4.4. Quantile Mapping

Quantile mapping is a commonly used method for correcting statistical biases in datasets. One study utilizing this method was conducted by Gowan & Horel [46], who evaluated IMERG-E precipitation estimates using regional quantile mapping to anticipate wildfires in Alaska. Additionally, Cannon [47] applied multivariate quantile mapping to correct various climate indicators, which were subsequently used to calculate the Canadian Fire Weather Index (FWI). The study found that multivariate bias correction via n-dimensional PDF (MBCn) performed better than univariate bias correction and multivariate bias correction using Pearson or Spearman correlations.

3.4.5. Empirical Orthogonal Function (EOF)

Empirical Orthogonal Function (EOF) is a method used to classify the primary patterns within a dataset. Zhong et al. [48] utilized EOF alongside two other pattern classification methods, Composite and Self-Organizing Map (SOM), to analyse synoptic weather patterns associated with 203 wildfires that burned 50,000 acres (20,250 ha) or more and 80 wildfires that burned 100,000 acres (40,500 ha) or more in Northwestern United States between 1984 and 2014.

3.5. Recommendations

This systematic literature review (SLR) is designed to examine studies related to forest and land fire analysis, also referred to as forest fire or wildfire, that utilize methods from mathematics, statistics, and computer science. Based on the classification and synthesis of several recent articles, several methods have been widely applied in forest fire data analysis, particularly common methods such as correlation, regression, classification, clustering, and artificial neural networks. However, several methods remain underutilized, including copula, fuzzy inference, image recognition, quantile mapping, and empirical orthogonal function (EOF). These methods are especially rare in forest fire analysis in Indonesia. This study provides recommendations for researchers to guide future studies on forest fire analysis.

EOF is still rarely used, especially in Indonesia. Researchers could explore the relationship between forest fires and other indicators such as temperature, soil type, cloud cover, wind direction, and more. Additionally, they could compare pattern classification results—also referred to as dimensionality reduction—using EOF with other classification methods such as Composite and Self-Organizing Map (SOM). Moreover, quantile mapping remains an evolving method, as indicated by the growing number of publications on this topic. The synthesis of several studies suggests that numerous advancements in quantile mapping can be applied for bias correction in datasets. One promising approach is multivariate bias correction, which can correct biases across multiple climate indicators while accounting for their interrelationships. On the other hand, copula is a rapidly emerging and widely discussed method. Researchers can leverage copula methods to analyze joint distributions or assess the dependency between various climate indicators and forest fire occurrences.

4. Conclusion

The application of mathematical, statistical, and computer science methods in wildfire analysis has grown significantly from 2000 to 2025, with an annual research growth rate of 8.16%. A surge in publications occurred after 2010, peaking between 2022 and 2024, driven by the convergence of several factors—including advancements in computational technologies, the increasing frequency and severity of wildfire events due to climate change, and a global shift in research priorities toward environmental sustainability and disaster resilience. Research output is widely distributed across SCImago Journal Rank (SJR) quantiles, indicating both widespread academic interest and a growing recognition of wildfire research as a high-impact topic. This distribution suggests that high-quality academic outlets are prioritizing wildfire research. Leading journals in the field include Remote Sensing, Science of the Total Environment, and International Journal of Wildland Fire, along with interdisciplinary sources such as Atmospheric Environment and Fire. These trends indicate a shift toward more sophisticated analytical approaches to wildfire prediction and management, integrating environmental, geospatial, and computational perspectives.

The most widely used techniques in wildfire analysis are correlation, regression, classification, clustering, and artificial neural networks, which help model wildfire occurrences and predict fire-prone areas. However, several advanced methods remain underutilized, including copula, fuzzy inference, image recognition, quantile mapping, and empirical orthogonal function (EOF). These methods offer significant potential for refining data processing techniques and improving predictive accuracy. Future research should explore copula functions to model dependencies between wildfire-related variables, fuzzy inference for classification improvements, and image recognition for automated fire detection. Quantile mapping can enhance bias correction in climate datasets, while EOF can identify dominant wildfire patterns and improve classification models. Expanding the use of these techniques, particularly in regions like Indonesia, could lead to more accurate wildfire forecasting and better disaster preparedness, ultimately strengthening wildfire management strategies. Overall, this review contributes to the field by mapping the evolution of wildfire research methods, highlighting underutilized yet promising techniques, and providing a foundation for future interdisciplinary studies that aim to improve wildfire prediction and management.

Author Contributions. **Mohamad Khoirun Najib**: Conceived the study, designed the methodology, conducted the analysis, curated the data, and wrote the original draft. **Sri Nurdiati**: Contributed to the conceptualization, validated the methodology, supervised the research, and reviewed and edited the manuscript. Both authors have read and agreed to the published version of the manuscript.

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