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Review

Fire Detection with Deep Learning: A Comprehensive Review

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Abstract: Wildfires are a critical driver of landscape transformation on Earth, representing a dynamic and ephemeral process that poses challenges for accurate early detection. To address this challenge, researchers have increasingly turned to deep learning techniques, which have demonstrated remarkable potential in enhancing the performance of wildfire detection systems. This paper provides a comprehensive review of fire detection using deep learning, spanning from 1990 to 2023. This study employed a comprehensive approach, combining bibliometric analysis, qualitative and quantitative methods, and systematic review techniques to examine the advancements in fire detection using deep learning in remote sensing. It unveils key trends in publication patterns, author collaborations, and thematic focuses, emphasizing the remarkable growth in fire detection using deep learning in remote sensing (FDDL) research, especially from the 2010s onward, fueled by advancements in computational power and remote sensing technologies. The review identifies "Remote Sensing" as the primary platform for FDDL research dissemination and highlights the field's collaborative nature, with an average of 5.02 authors per paper. The co-occurrence network analysis reveals diverse research themes, spanning technical approaches and practical applications, with significant contributions from China, the United States, South Korea, Brazil, and Australia. Highly cited papers are explored, revealing their substantial influence on the field's research focus. The analysis underscores the practical implications of integrating high-quality input data and advanced deep-learning techniques with remote sensing for effective fire detection. It provides actionable recommendations for future research, emphasizing interdisciplinary and international collaboration to propel FDDL technologies and applications. The study's conclusions highlight the growing significance of FDDL technologies and the necessity for ongoing advancements in computational and remote sensing methodologies. The practical takeaway is clear: future research should prioritize enhancing the synergy between deep learning techniques and remote sensing technologies to develop more efficient and accurate fire detection systems, ultimately fostering groundbreaking innovations.

Keywords: deep learning; forest fire detection; forest fire; wildfire; wildfire detection

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1. Introduction

In recent years, climate change and human activities have significantly impacted the environment, leading to more frequent and severe extreme events such as heat waves, droughts, dust storms, floods, hurricanes, and wildfires [1–3]. Among these events, wildfires have been especially damaging, harming ecosystems and infrastructure, and posing risks to human life [4,5]. Therefore, it is crucial to detect and monitor wildfires promptly and effectively across large areas, including type, extent, and impact [6–8].

Forests play a vital role in maintaining ecological balance and contributing to the global carbon cycle. They provide habitats for diverse plant and animal species and offer various benefits to humans [8–10]. However, wildfires, deforestation, and clear-cutting pose serious threats to these ecosystems, leading to biodiversity loss, soil degradation, and increased greenhouse gas emissions [9,11–14].

Historically, forest fire detection methods relied on human observation from fire lookout towers and basic tools. However, these methods are inefficient and prone to human error and fatigue. Conventional sensors that detect heat, smoke, flames, and gases encounter delays, and their coverage area is limited, requiring multiple units for effective monitoring [6,15,16].

Advancements in computer, machine learning, remote sensing, and sensor technology have led to new methods for detecting and monitoring forest fires. These developments have improved the effectiveness of sensors in recognizing active fires. This paper focuses on key forest fire detection systems that utilize optical remote sensing, digital image processing, and advanced classification methods [6,17,18].

Forest fire detection systems can be classified into terrestrial, aerial, and satellite-based systems based on their level of acquisition. These systems are equipped with visible, infrared, or multispectral sensors to collect data, which are then analyzed using machine learning techniques [6,19]. Although terrestrial environments are useful for local monitoring, they have limitations in terms of coverage and speed of response. Satellite systems offer extensive coverage and are valuable for large-scale surveillance and the long-term assessment of fire impacts [6,16,20,21].

Given the increasing severity of climate-related events, there is an immediate need for advanced forest fire detection systems [6,16,20,21]. By integrating cutting-edge technologies, such as deep learning and remote sensing, we can enhance the early detection and control of forest fires, reducing their destructive impacts on ecosystems, infrastructure, and human lives. It is crucial for researchers to focus on developing efficient machine learning algorithms and classification techniques in order to improve the accuracy of forest fire detection systems [6,8].

This study utilizes a variety of review methods to examine patterns in academic literature regarding fire detection using deep learning in remote sensing (FDDL). By combining both quantitative and qualitative studies, this mixed-type literature review provides a comprehensive perspective on the subject [22–25]. The goal of this analysis is to further explore current research, uncover additional perspectives and advancements, and incorporate diverse methodologies to strengthen our comprehension of the scientific field concerning fire detection with deep learning techniques in remote sensing.

This study employs a diverse range of review methods, including mathematical, statistical, and literature analysis, to examine trends in academic literature. This unique mixed-method approach not only offers valuable insights into scientific fields such as fire ecology, but also piques curiosity by providing a comprehensive understanding of the progression and impact of research across disciplines [22–25]. By combining qualitative and quantitative tools in the analysis, we are able to gain comprehensive insights into patterns in the field of FDDL science, thereby identifying critical research areas and knowledge gaps. This understanding can further promote advancements in fire detection using deep learning techniques from various methodologies and perspectives.

Our primary objective is to conduct a comprehensive review of the advancement of remote sensing technologies within the realm of FDDL. This review will primarily focus on deep learning methodologies employed in remote sensing research for fire detection, encompassing prevalent deep learning architectures utilized in FDDL, commonly employed sensor systems in FDDL studies, and the geographical locations where these studies have been conducted. Our aim is to provide an in-depth exploration of these critical aspects.

Additionally, our investigation will extend to the identification of countries that have significantly influenced research in this field and the recognition of prominent patterns within scholarly work, including the evolution of these patterns over time. A comprehensive understanding of the leading researchers and influential publications in this field is essential to fully comprehend the research landscape and advance the field of FDDL. This review will offer practical suggestions and insights to guide future research endeavors in utilizing deep learning methods for fire detection within the remote sensing scientific community.

2. Materials and Methods

We utilized a comprehensive methodological approach that integrates traditional bibliometric analyses with qualitative and quantitative characteristics, as well as elements of systematic review methods, including a detailed examination of paper sections for information retrieval. In essence, we employed diverse analytical techniques to deepen our understanding of the topic. Additionally, we investigated the co-occurrence network to identify trends related to advancements in fire detection using deep learning in remote sensing. Detailed procedures will be provided in the forthcoming sections.

In the first stage, we completed the following steps: selecting a database, formulating search terms, and applying filters. Initially, we utilized the Scopus database and identified key semantic terms associated with the FDDL scientific domain. These terms were then used to construct our search query. Afterward, we carried out an initial search and applied constraints to exclude non-peer-reviewed literature such as reviews, conference proceedings, book chapters, and books. This refining process resulted in a subset of the original dataset that only included papers published up to 2023 to prevent duplicate content from multiple publication sources.

From this enhanced dataset, we initiated a stringent manual screening procedure. We meticulously reviewed the titles and abstracts of all papers to validate their pertinence to our assessment of the FDDL field. In cases where the relevance was not immediately clear, we conducted a full reading to ensure concordance with our research objectives. This thorough screening process, which involved multiple reviewers, ensured the precision of our research findings.

In the first phase, we examined a particular dataset of literary information and conducted extensive examinations. These encompassed overall statistical findings and condensed outcomes, scholarly output unique to various nations, network scrutiny for joint occurrences, patterns in publication trends, developing subjects over time, alterations in author productivity over time, and cooperative activities among countries.

To enrich our dataset, we thoroughly analyzed the most cited articles, representing approximately 50% of the selected articles. This study aimed to identify the dominant trends in FDDL, and we employed systematic review methods for this investigation. The articles were selected based on their citation count, which indicates their significant influence in the field of FDDL. Each article underwent thorough evaluation, and we condensed important details such as the type of model utilized and its components, variables, data presentation methods, research location, and total number of citations.

This approach afforded us a thorough insight into the most influential research and its significance in the field. Table 1 and Figure 1 outline the research inquiries, data origins, and methodologies employed in this study to improve the clarity of our analyses.

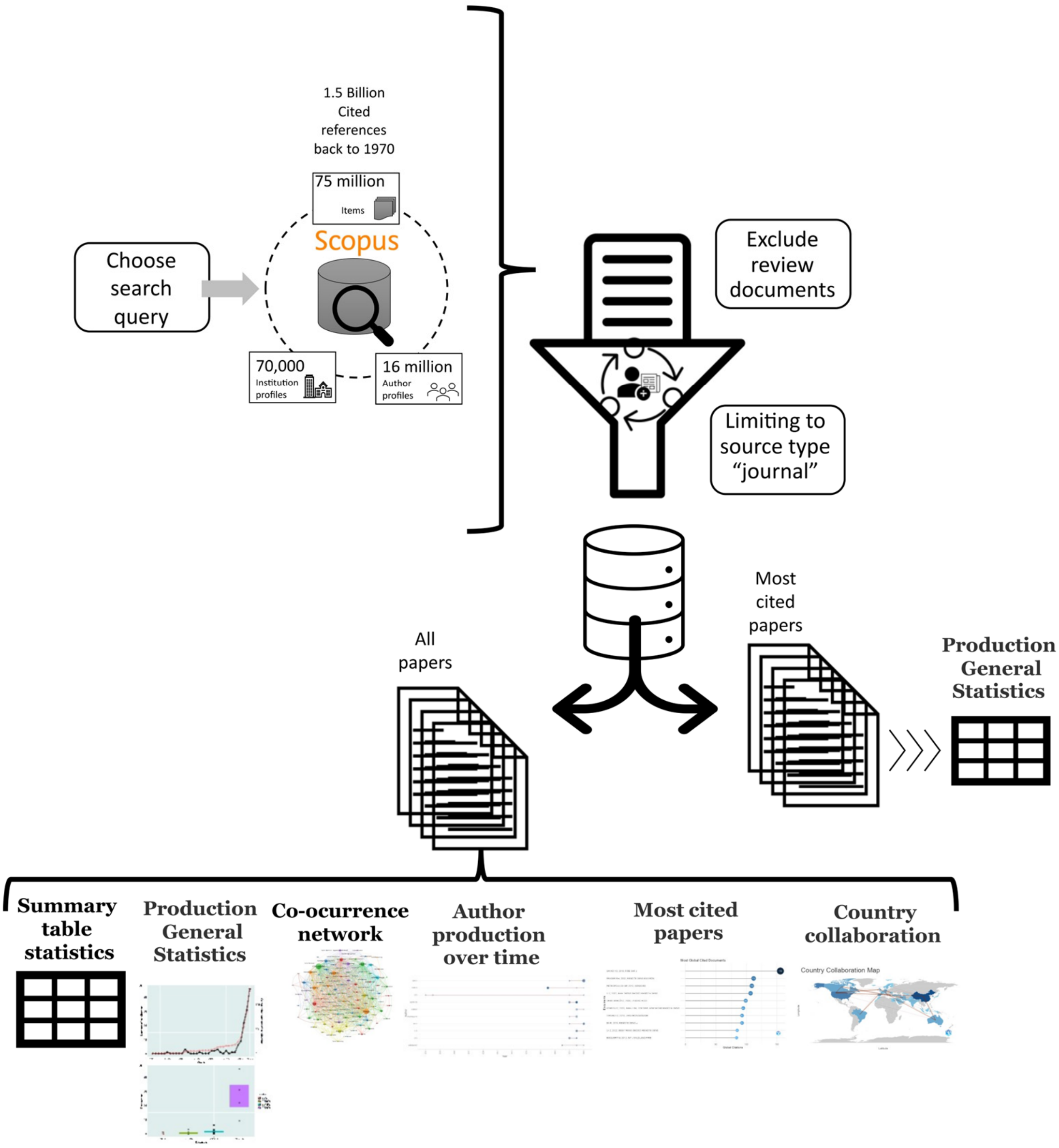

Figure 1. The diagram depicts the series of steps carried out at each phase of the investigation.

Table 1. This table provides a concise summary of the connections between the research inquiries, data sources, and analytical methods utilized in this study.

	Questions	Analysis	Source Data
1.	What are the patterns of publication trends in the field of FDDL studies?	General statistics	All papers
2.	Which journals have the highest prominence based on the quantity of articles published in the FDDL field?	General statistics	All papers
3.	Which countries lead as producers in the scientific field of FDDL?	General statistics	All papers
4.	How extensive is collaboration between countries in the scientific field of FDDL?	General statistics	All papers
5.	What are major deep learning architectures frequently employed in FDDL research?	Reading and General analysis	Most cited papers
6.	What are the main themes, focal points, and approach utilized in FDDL studies?	Co-occurrence network	All papers

Table 1. *Cont.*

	Questions	Analysis	Source Data
7.	What sensor systems are most utilized in studies related to FDDL?	Reading and General analysis	Most cited papers
8.	Where have these studies been predominantly conducted geographically?	Reading and General analysis	Most cited papers
9.	What are the patterns of publication trends in the field of FDDL studies?	Reading and General analysis	Most cited papers

2.1. Data Base

Please make sure to keep the following text in mind: This study relied on the Scopus database, established by Elsevier in November 2004 [26]. Scopus is a comprehensive bibliographic platform that encompasses a wide range of scientific literature and incorporates citation analysis data dating back to 1996. It encompasses over 53 million published references from more than 24,000 scientific journals [26]. This web-based system provides a variety of tools for efficient literature searches using both basic and advanced queries, facilitating quick and consistent information retrieval to offer a comprehensive overview of scientific domains [26]. These attributes influenced our decision to use Scopus as the primary source of literature for this study (see Figure 1). Our goal was to achieve a thorough understanding of our research topic by making use of this resource.

2.2. Search and Screening Process

We carefully crafted a search string by choosing particular terms, expressions, and Boolean operators to guarantee the retrieval of the most precise outcomes. This search string played a crucial role in shaping our initial search approach. For our investigation, we employed the subsequent search query to ensure the thorough inclusion of pertinent literature: TITLE-ABS-KEY ((“Forest fire” OR “Wildfire” OR “Vegetation fire” OR “Fire” OR “Smoke” OR “Burned area” OR “Bushfire” OR “Fire regime” OR “burn scar”) AND (“Deep learning” OR “Neural networks” OR “Artificial intelligence”) AND (“Detection” OR “Segmentation” OR “Map*” OR “Classification” OR “Recognition” OR “Identification” OR “Predicting”) AND (“Remote sensing” OR “Satellite imaging” OR “Remote observation”)) AND PUBYEAR > 1960 AND PUBYEAR < 2024 AND (LIMIT-TO (SRCTYPE, “j”)) AND (LIMIT-TO (PUBSTAGE, “final”)) AND (LIMIT-TO (DOCTYPE, “ar”)).

The screening process involved a comprehensive review of all titles and abstracts to determine their relevance to the FDDL scientific field. In cases where there was uncertainty about a paper’s relevance, the entire paper was thoroughly scrutinized. Papers that were deemed irrelevant, such as gray literature and review articles, were not considered. Furthermore, conference proceedings, book chapters, and books were intentionally excluded to narrow down the focus to a more specific subset of FDDL-related papers published until 2023. This approach was designed to prevent redundancy resulting from the same content being presented in multiple formats. The subsequent analysis aimed to identify the most frequently cited papers as authoritative sources.

2.3. General Analysis

We utilized the advanced capabilities of the Bibliometrix 3.1.4. [27] package and VOSviewer 1.6.17 software for our quantitative analysis and the creation of a co-occurrence network of terms [28–31]. Bibliometrix is a powerful statistical tool specifically designed for scientometric and bibliometric data examination [27]. Moreover, VOSviewer is a specialized tool for bibliometric analysis and visualization, providing a comprehensive view of various attributes in scientific publications, such as journals, as well as researchers, institutions, countries, keywords, and abstracts [27–31].

To construct the co-occurrence networks of terms, we integrated information from the titles, abstracts, and keywords of the articles [27–31]. Using VOSviewer 1.6.17, we utilized the "map based on text data" feature and employed bibliographic database files. We employed a binary counting algorithm to count minimum five occurrences of words and terms and created a synonym file to address semantic errors caused by redundancy. We established a minimum threshold of ten occurrences for constructing the co-occurrence network, including all terms and words in the analysis [27–31].

For the examination of author productivity, scientific output by country, international collaborations, temporal trends, co-authorship patterns, author productivity over time, highly referenced articles, and publication impact in research evaluation and bibliometrics, we leveraged the Bibliometrix library to extract valuable insights [27].

We selected 50% of all papers identified during the screening phases to undergo a systematic elements approach. We meticulously gathered information by conducting an in-depth and extensive evaluation of each chosen paper, ensuring that all data originated directly from the relevant articles. This thorough process allowed us to extract comprehensive insights for our analysis.

All data analysis and statistical procedures were meticulously carried out using R version 4.0.4 [32], RStudio IDE version 1.4.1106 [33,34], and ggplot2 version 3.3.5 [35].

3. Results

3.1. Publishing Trends

Following the implementation of filters, the screening and refining of the bibliographic database, and a thorough literature review, we identified 132 published papers on FDDL. Additional comprehensive details can be found in Table 2, Figure 2, Table S1, and the Supplementary Materials. Most of these publications are from recent decades, particularly from the 2010s to 2020s, accounting for 18 and 108 papers, respectively, which make up approximately 95.45% of all published articles related to FDDL. It is noteworthy that only a small percentage (4.55%) of all FDDL-related publications were produced between the early 1990s and 2000s.

Our comprehensive analysis of publication patterns spanning over three decades, from 1990 to 2023, unearthed a crucial trend. The annual output of articles related to FDDL experienced significant fluctuations, with a remarkable surge in interest and research on this topic, particularly from the 2010s onwards. This upward trajectory in FDDL research is intricately tied to the rapid advancements in computational and remote sensing technologies, underscoring the importance of our findings.

Table 2. The table contains general statistics on production sources, authors, and collaborations in decades of FDDL-related publications.

Timespan	**1990–1999**	**2000–2009**	**2010–2019**	**2020–2023**	**1990–2023**
Sources (journals)	1	4	11	45	52
Papers	1	5	18	108	132
Annual growth rate %	0	−19.7	12.98	72.25	14.65
Paper contents					
AUTHORS					
Authors	2	11	70	489	568
Authors of single-authored docs	0	0	0	2	2
Author collaborations					
Single-authored docs	0	0	0	2	2
Co-authors per doc	2	2.6	4.22	5.29	5.02
International co-authorships %	0	40	22.22	34.26	32.58

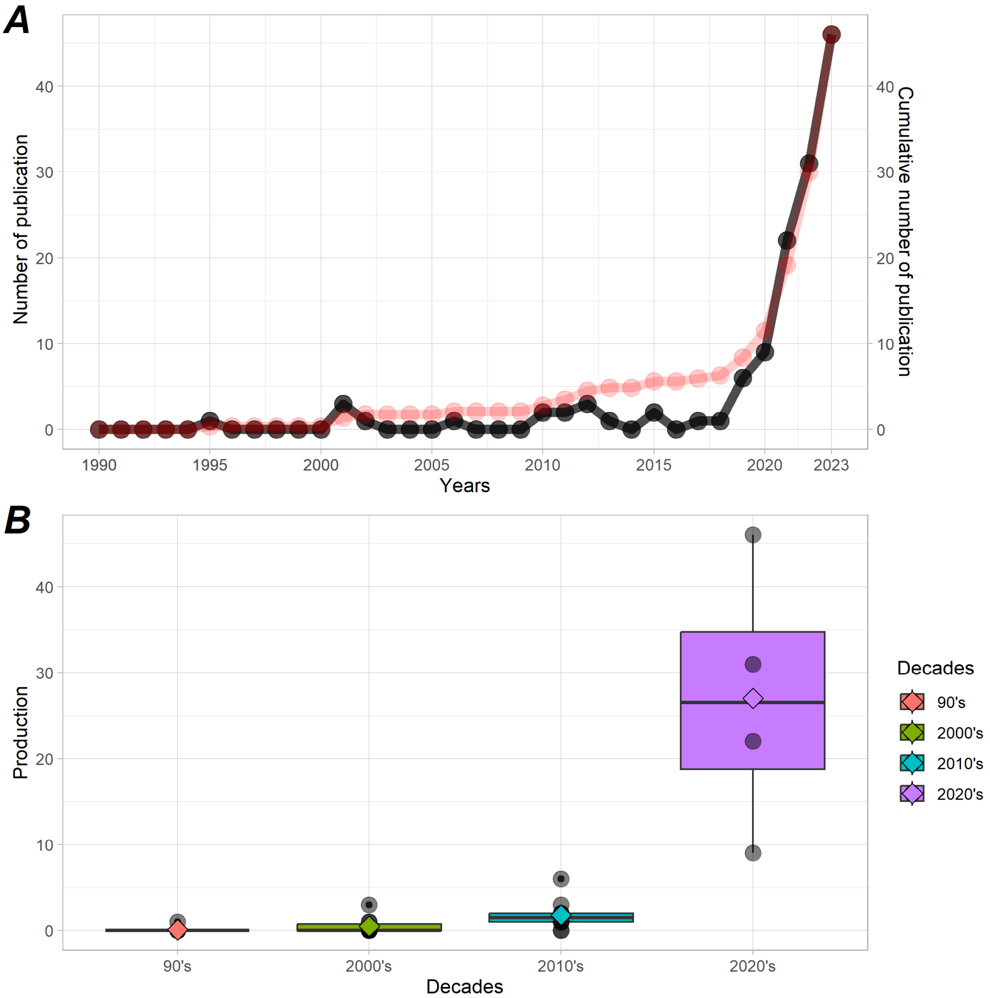

Figure 2. The yearly increase in FDDL publications (represented by the black curve on the left y-axis) is contrasted with the cumulative yearly growth (illustrated by the red curve on the right y-axis) of the database from 1990 to 2023. (**A**) Shows the data associated with the Annual growth rate FDDL. Production across decades is depicted in (**B**), using different colors for each decade.

Upon analyzing the data, we found that the average annual publication of research papers on FDDL has been 3.86 since the initial paper was published in 1995, with a standard deviation of 10.5. In the 1990s, the average was a modest 0.2 with a deviation of ±04.44. In the 2000s, 0.5 ± 0.9, and in the 2010s, it rose to 1.8 ± 1.75. Finally, in the 2020s, it increased significantly to about 27 papers per year, with a standard deviation of 15.56 (refer to Figure 2B for details).

The highest numbers of published papers were recorded in 2023, 2022, 2021, 2020, and 2019, with 46, 31, 22, 9, and 6 articles, respectively (Figure 2A). These years are significant because they indicate periods of increased research activity in the field of FDDL, potentially due to technological advancements, policy changes, or emerging research trends. There has been a visual increase in the number of publications since the late 2010s, particularly after 2019 (Figure 2A).

The analysis of growth rate statistics for published papers reveals a clear pattern between decades: apart from stagnant growth in the 2000s, all other periods show an upward trend. Remarkably, the most substantial growth was observed between 2020 and 2023, with an impressive growth rate of 72.25%. This represents an almost fivefold increase compared to the overall growth rate of 14.65% observed from 1990 to 2023 (Table 2).

After analyzing the quantity of authors per decade, it becomes apparent that there is a distinct trend as the number of papers increases. At the same time, there is a rise in the number of contributing authors, especially in recent decades. As an example, the periods spanning from 2010 to 2019 and from 2020 to 2023 displayed the highest author counts, with 70 and 489 contributing authors, respectively. The metric measuring co-authors per paper showed peak values of 4.22 and 5.29 during these periods, indicating a significant increase in research collaboration. Moreover, there was a notable uptick in international cooperation, with the highest percentage of co-authorships (40%) occurring between 2000–2009. It is worth noting that there was a decrease in co-authorships from 2010 to 2019, followed by an increase from 2020 to 2023 compared to the previous decade, although the values were lower than those observed in the 2000s (Table 2).

3.2. Co-Occurrence Networks

Figure 3 shows a co-occurrence network presenting the different subjects and research methods utilized by authors in the FDDL literature. Covering the period from 1990 to 2023, the network consists of 112 elements, which, in this context, refer to specific research topics or methods, grouped into eight clusters. The top 10 most common terms, which are the most frequently occurring research topics or methods, comprise approximately 38.5% of the entire network.

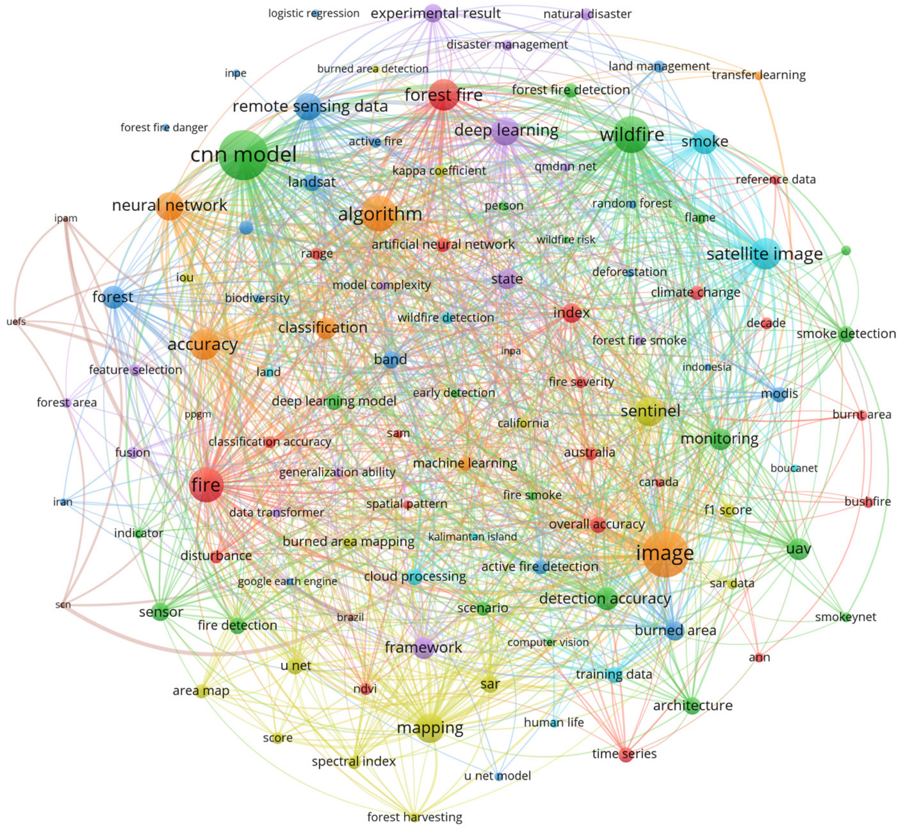

Figure 3. An analysis of word co-occurrence networks was conducted on titles, abstracts, keywords, and general paper information spanning from 1990 to 2023.

Each cluster in the co-occurrence network represents a set of related methods and themes, categorized based on similarities in their research focus. The largest cluster, positioned in the center, embodies a central theme within the research field, while the subsequent clusters represent progressively smaller yet significant areas of study. The arrangement of elements in these clusters not only underscores the field's diversity, but also showcases the vast scope of research topics that the FDDL field encompasses.

A clear pattern emerged from the co-occurrence network analysis, indicating how items are spread across the five clusters. The first cluster had the highest number of items at 23, followed by 20 items in both the second and third clusters, 19 in the fourth cluster, and

15 in the fifth cluster. This distribution implies that specific research topics and methods are more interconnected within the FDDL literature, while others are less prevalent. The higher the number of items in a cluster, the more prevalent and interconnected the research topics and methods within that cluster are. Overall, the co-occurrence network analysis illustrates the substantial evolution and diversification of the FDDL field over time.

Based on their representativeness, let us look at each of the five main clusters dealing with various FDDL related issues.

- Cluster 1: The primary focus of the first cluster lies in methodological approaches, experimental results, and CNN model.
- Cluster 2: The second cluster is centered on fire severity, time series, classification accuracy, and ANN model.
- Cluster 3: This cluster details aspects of the U-Net model, active fire detection, forest danger fore, Google Earth Engine, and land management.
- Cluster 4: This cluster includes disaster management, experimental results, model complexity, and neural networks.
- Cluster 5: The emphasis is on burned area detection, burned area mapping, kappa coefficient, SAR data, Sentinel data, and spectral index.

3.3. Country Collaboration

The top five countries collectively account for 60.3% of the total global scientific output. China leads the group, with a contribution of 24.8%, followed by the United States at 15.1%. South Korea holds the third position with an 8.6% share, while Brazil and Australia closely follow, contributing 7.6% and 5.0%, respectively.

Figure 4 visually represents the extent and quality of partnerships among nations, showcasing collaborations between authors and institutions. The varying thickness of the lines in the graphic indicates the strength of these connections, offering essential insights into collaborative efforts within the FDDL research field. It highlights substantial engagement in joint research and knowledge exchange across countries, demonstrating proactive international collaboration.

Figure 4. The figure demonstrates the collaboration network, depicting the co-authorship of published works by authors from various countries. The red lines denote collaborative efforts between authors from different nations, with line thickness reflecting the frequency of these collaborations.

These collaborations, as depicted in Figure 4, are instrumental in fostering the exchange of ideas, resources, and expertise among researchers worldwide. They are a testament to the global impact of the FDDL field and its ability to bring together diverse perspectives and knowledge.

The collective scientific output of the top five countries accounts for 62.3% of global partnerships. The United States and China are major participants, responsible for 19.6% and 18.0% of total collaborations, making up 37.7% of overall collaborative activities. Brazil also has a significant impact at 9.8%, while Germany and Canada are noteworthy contributors at 8.2% and 6.5%, respectively. This analysis provides a comprehensive evaluation of international collaborations, offering insights into the level of participation of each country and its role in global partnerships.

3.4. Most Cited Papers

Upon further analysis of the most cited papers, it was found that just 32.7% of all references were linked to the top 10 papers, with a substantial total of 3162 citations, as shown in Figure 5.

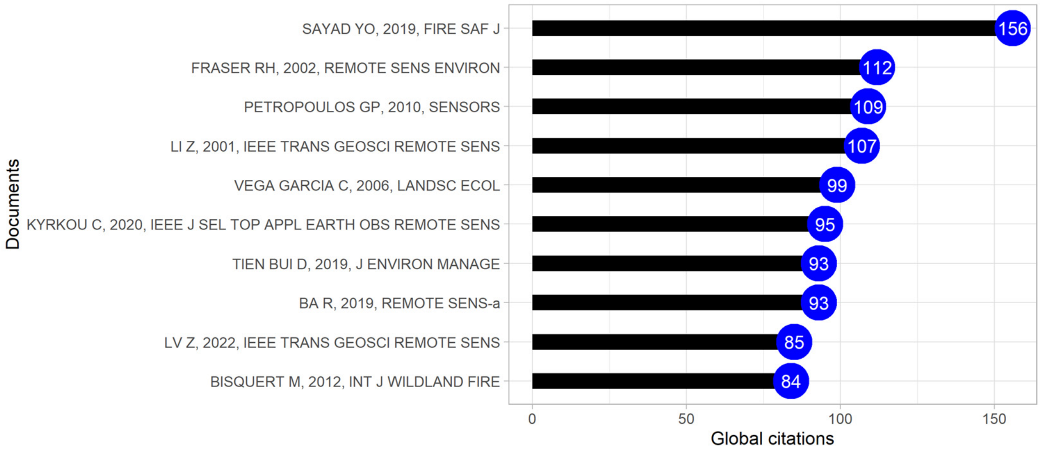

Figure 5. The figure illustrates the top ten most impactful papers based on total citations. The respective citation numbers are represented by blue circles on the right side.

A fraction of the academic literature commands a substantial amount of attention and impact in its field. This raises concerns about potential biases and prevailing trends. Further scrutiny reveals that a select few highly referenced papers hold significant sway, potentially shaping the trajectory of research and the collective knowledge within the field.

When analyzing the top ten most cited papers, an interesting pattern emerged in their connection to specific years and decades. Notably, half of these papers were released in the 2010s, focusing on 2010, 2012, and 2019. Collectively, these garnered 535 references, which accounts for approximately 16.9% each.

During the 2000s, specific years such as 2001, 2002, and 2006 (as shown in Figure 5) emerged as pivotal periods of intense research activity within the discipline. This observation underscores the dynamic nature of research and the shifting areas of focus over time. A closer examination of the most frequently cited papers revealed a concentration in more recent years, particularly in the 2010s. This emphasis on recent research activity further illustrates the evolution of key areas of interest within the field of FDDL.

3.5. Influential Journals

The analysis in Figure 6 offers a comprehensive overview of the distribution of publications on FDDL across various journals. It reveals that 52 journals have actively contributed to the knowledge in this field, with the top 10 journals playing a significant role. Notably, *Remote Sensing* stands out as the leader with an impressive 28 articles, accounting for approximately 21.2% of all publications (see Figure 6). The dominance of this journal in the field is quite evident. Following this, *IEEE Transactions on Geoscience and Remote Sensing* published ten articles, representing around 7.6% of the total output. In third place is *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, with eight articles, constituting about 6.1% of the overall body of work on FDDL.

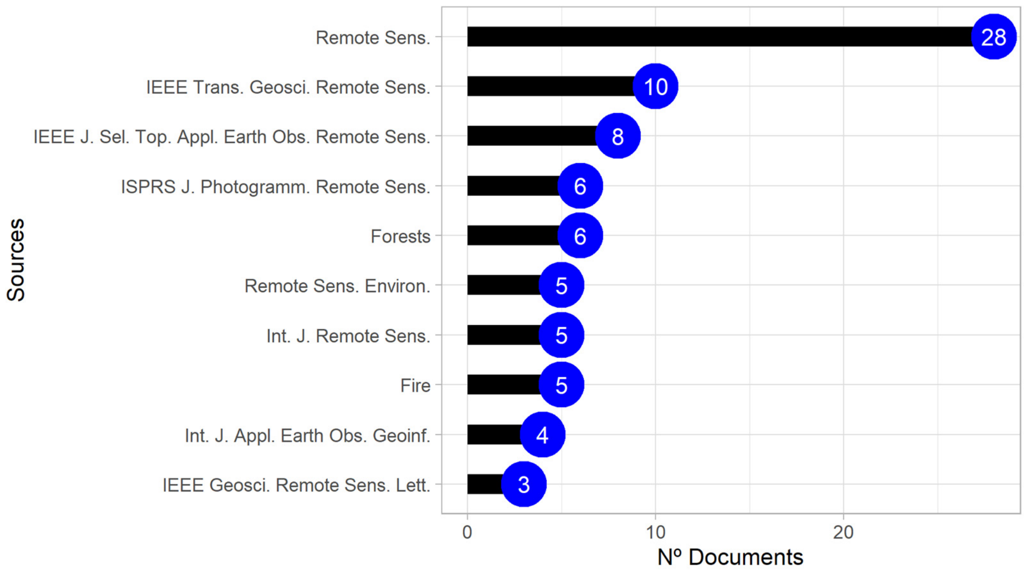

Figure 6. The figure displays the top ten most impactful journals based on total citations, with the respective citation numbers indicated by blue circles on the right side.

A total of six articles, approximately 4.5% each, were contributed by the journals *Forests* and *ISPRS Journal of Photogrammetry and Remote Sensing*. The journals *Fire*, *International Journal of Remote Sensing*, and *Remote Sensing of Environment* each published five articles, collectively accounting for about 3.8% of the overall content individually. Additionally, the journal *International Journal of Applied Earth Observation and Geoinformation* released four articles, constituting about 3.0% individually. Lastly, *IEEE Geoscience and Remote Sensing Letters* featured three articles, representing roughly 2.3% collectively.

3.6. Author Contributions

When analyzing Figure 7, we can observe the top 10 authors who have published the most in the context of FDDL. Our analysis of the selected articles revealed the presence of 568 different authors, with an average of 5.02 authors per article, but only two articles had a single author. The top five most prominent authors were Ban Y., who ranked first with five papers, representing 0.76% of the analyzed articles; Chen J., Li Z, and Seydi St, with four papers and approximately 0.6% for each; and Chen S., with three papers, which accounts for approximately 0.45% (Figure 7).

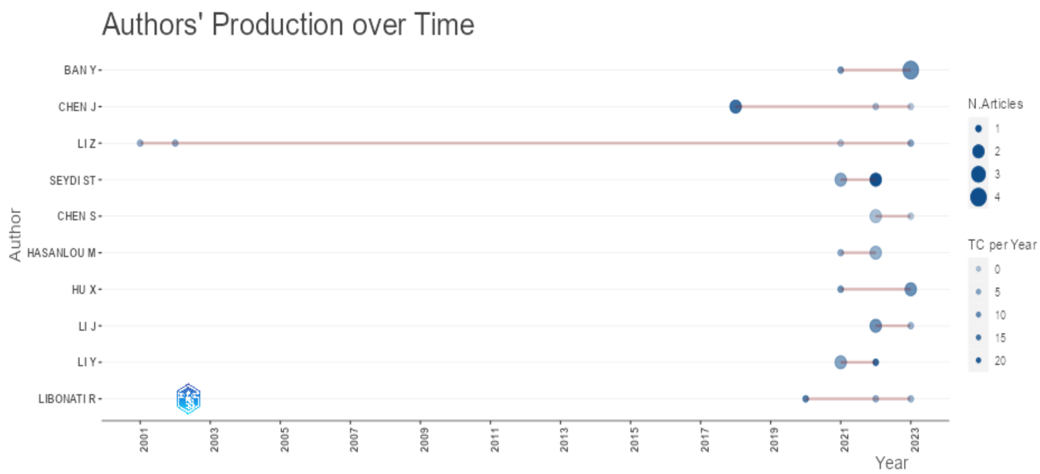

Figure 7. Temporal trends of key authors are visualized using a blue circle to represent the number of published papers, and red lines to show the temporal trends of papers published over time for each author.

Based on the analysis of the time patterns of authors in the FDDL, it is evident that the principal authors should have consistently published articles over time, showing variable productivity, especially before the 2020s. The only author who diverged from this pattern was Li Z., who consistently produced work from the 2000s up to the 2020s. The most prolific authors concentrated their highest volume of articles in specific years during the 2020s. However, as shown in Figure 7, these authors consistently maintained a steady production level, particularly during the 2020s. This sustained productivity suggests that interest in FDDL is more recent and does not indicate enduring support or continuous contributions to this field between the 1990s and 2020s.

3.7. Trends in the Most Influential Publications

The review of most influential papers provides an overview of various architectures tailored to specific tasks such as classification, detection, segmentation, and their combinations. Classification tasks in forest fire detection involve identifying whether an image contains fire or non-fire elements. Several architectures have been prominently used for this purpose. The InceptionV3 model, known for its efficiency in handling image classification tasks, was employed to classify satellite images of forest fires. Similarly, ResNet and VGG architectures, known for their deep layers and robust feature extraction capabilities, were utilized in various studies. Examples include ResNet variants, making them suitable for real-time applications. Additionally, hybrid models that combine Convolutional Neural Networks (CNN) with Long Short-Term Memory (LSTM) or Gated Recurrent Units (GRU) showed improved performance in time-series data classification, highlighting their potential in predicting fire occurrences based on sequential data.

Object detection tasks focus on localizing and identifying objects within images. Architectures like YOLOv3 and YOLOv5 are extensively used due to their real-time detection capabilities and accuracy. YOLOv3-tiny, adapted for UAV-captured imagery, achieved significant detection rates, demonstrating the model's efficiency in aerial surveillance. These models are particularly effective in identifying small fire instances, crucial for early intervention. The integration of CNN also proved beneficial in reducing false alarms, thereby increasing the reliability of detection systems.

Segmentation tasks aim to delineate fire-affected regions within an image. U-Net and its variants, such as F-Unet, are widely used due to their encoder–decoder architecture, which facilitates precise boundary detection. Fire-Net, developed using Landsat-8 RGB and thermal images, showed exceptional accuracy in segmenting active fire regions, making it a valuable tool for detailed fire mapping. The use segmentation tasks demonstrated the model's capability to operate efficiently with limited computational resources while maintaining high accuracy.

Combining detection and classification tasks allows for robust fire monitoring systems. Architectures like YOLO integrated with VGG or other CNN models have shown remarkable performance. The use of transfer learning techniques to initialize models enhances their ability to identify smoke and flames accurately. For instance, a combined YOLO + VGG model achieved high accuracy by leveraging data augmentation techniques to expand the training dataset, thus preventing overfitting and improving generalization.

Segmentation and classification tasks, when combined, provide comprehensive fire detection and analysis. Models that integrate segmentation capabilities with classification tasks can not only identify the presence of fire, but also delineate the affected areas. The use of advanced architectures such as PSPNet and DeepLab in segmentation tasks ensures high precision in identifying fire boundaries, while classification models like DenseNet further refine the categorization of fire severity and spread.

The potential of generative adversarial networks (GANs) in augmenting training datasets and improving model generalization is also noted, pointing towards future research directions in this domain.

Overall, the integration of deep learning methods in forest fire detection systems shows immense potential in enhancing early detection, reducing false alarms, and providing a detailed analysis of fire-affected regions.

4. Discussion

Our research employed a mixed review methodology to thoroughly analyze the progress in remote sensing technologies for FDDL. As illustrated in Figure 2A, we reviewed 132 academic papers on the application of deep learning in fire detection from 1990 to 2023, uncovering a significant trend in fire detection and deep learning research over the past three decades. The results uncovered notable trends and insightful perspectives on this field's development and current status. This section delves into the implications of these findings by exploring patterns in publication frequency, author participation, collaborative initiatives, and thematic focus, underscoring their relevance for future FDDL research.

An exciting trend is the significant rise in FDDL publications, especially since the 2010s. As shown in Figure 2B, the number of FDDL-related publications has risen sharply, increasing from 18 in the 2010s to 108 in the 2020s, representing an overwhelming 95.45% of the total publications in this field. This growth reflects the growing acknowledgment of the importance and potential of FDDL. The surge can be attributed to advancements in computational power and remote sensing technologies, which have enabled the application of deep learning to complex tasks such as fire detection. The publication rate, which increased from an average of 0.2 papers per year in the 1990s to 27 documents per year in the 2020s, underscores the mounting interest and rapid progress in this field.

The analysis of publication sources highlights the significant role of specific journals in disseminating FDDL research. As shown in Figure 6, the distribution of publications on FDDL is comprehensively outlined, with *Remote Sensing* emerging as a prominent focus, comprising 28 articles, or approximately 21.2% of the total publications. Furthermore, respected journals such as *IEEE Transactions on Geoscience and Remote Sensing* and *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* underscore the preference for reputable remote sensing and geoscience platforms. This suggests that researchers prioritize reaching a specialized audience interested in advanced sensing and computational techniques.

The analysis of the FDDL research community revealed significant collaboration trends, as shown in Table 2. With an average of 5.02 authors per paper and a scarcity of single-authored articles, collaboration is integral to the nature of this field. Noteworthy researchers, including Ban Y., Chen J., Li Z., and Seydi St., have made substantial contributions, particularly in the 2020s. This collaborative effort reflects a dynamic and constantly evolving field that benefits from the integration of diverse expertise.

Additionally, the analysis of co-occurrence networks has provided a more comprehensive understanding of the primary research themes and methodologies in FDDL, as illustrated in Figure 3. The study revealed diverse specialized areas, spanning technical approaches such as CNN and ANN models to practical applications like active fire detection and land management. This diversity underscores the expanding scope of the field, addressing various aspects of fire detection, from algorithmic enhancements to real-world implementations.

The analysis presented in Figure 4 highlights that international collaboration is primarily driven by five leading countries: China, the United States, South Korea, Brazil, and Australia. This global partnership has fostered innovation and knowledge sharing, particularly with the US–China alliance, accounting for 37.6% of all collaborative efforts. Additionally, the contributions from countries like Brazil, Germany, and Canada emphasize the far-reaching impact and influence of FDDL research.

Our findings also reveal that a small number of highly referenced studies have substantially impacted FDDL research, representing 32.7% of all citations. These studies likely influenced essential research directions and established fundamental methodologies that subsequent research has built upon. The high citation rates in recent years, particularly during the 2010s, reflect the rapid advancement of critical areas in FDDL, driven by technological progress and emerging research trends.

The analysis of influential FDDL papers showcases a range of architectural approaches for classification, detection, and segmentation tasks. Notably, InceptionV3, ResNet, and VGG models have demonstrated fire classification effectiveness. Furthermore, hybrid models that combine CNNs with LSTM or GRU architectures have improved time-series data performance. YOLOv3 and YOLOv5 stand out for their object detection due to their real-time capabilities, especially in processing UAV-captured images, as they effectively reduce false alarms and enhance reliability. Architectures like U-Net and Fire-Net are recognized in segmentation tasks for their precise boundary detection and efficient operation with limited resources.

The integration of detection and classification has given rise to robust fire monitoring systems. Models that merge YOLO with VGG have shown significant accuracy through transfer learning and data augmentation. Additionally, segmentation fusion with classification offers comprehensive fire detection and analysis. Advanced architectures such as PSPNet and DeepLab ensure high precision in this regard. The potential of generative adversarial networks (GANs) to enhance training datasets suggests exciting future research directions. Overall, the review underscores the efficacy of deep learning methods in improving early fire detection, minimizing false alarms, and providing detailed analysis. It emphasizes the necessity for continuous innovation and interdisciplinary collaboration to address wildfire challenges effectively. Additionally, it highlights the significance of refining these models through hyperparameter optimization, incorporating diverse data sources, and using advanced data augmentation techniques to enhance their practical utility.

The comparative assessment of deep learning models for fire detection highlights significant performance differences among various architectural approaches in effectively handling classification, detection, and segmentation tasks. For example, models like InceptionV3, ResNet, and VGG have demonstrated exceptional performance in fire classification tasks by leveraging their ability to extract deep features from complex imagery. Conversely, hybrid models that combine Convolutional Neural Networks with Long Short-Term Memory or Gated Recurrent Unit architectures have significantly improved handling time-series data, which is crucial for predicting fire occurrences based on temporal sequences. Additionally, YOLOv3 and YOLOv5 excel in object detection, particularly for their real-time capabilities, making them practical for processing UAV-captured images with minimal false alarms and enhancing the reliability of YOLO models for immediate fire detection in critical situations. On the other hand, U-Net and Fire-Net are preferred for segmentation tasks, excelling in precise boundary detection and efficient operation even with limited computational resources, making them suitable for large-scale fire mapping.

Significant progress has been made in integrating detection and classification tasks to develop more robust fire monitoring systems. For example, models that combine YOLO with VGG using techniques such as transfer learning and data augmentation have shown substantial improvements in accuracy, offering comprehensive fire detection solutions. Additionally, architectures like PSPNet and DeepLab are crucial in integrating segmentation with classification, resulting in high-precision fire analysis. Another notable advancement in the field is the utilization of generative adversarial networks to improve training datasets, which has the potential to enhance model generalization and performance in scenarios with limited labeled data. These advancements underscore the ongoing importance of refining deep learning models, optimizing hyperparameters, and integrating diverse data sources to improve fire detection systems' real-world applications and effectiveness.

Despite the significant progress in FDDL, several technical and practical limitations remain. One major challenge is the need for large, high-quality, and diverse datasets to effectively train deep learning models, especially when labeled data for fire events are scarce and imbalanced. Additionally, the computational demands for processing vast amounts of remote sensing data and running complex algorithms like CNNs and hybrid models can be prohibitive, particularly in real-time applications such as UAV-based fire detection.

One challenge lies in the ability of models to generalize, as many designs are sensitive to changes in environmental conditions, terrain, and fire behavior, leading to potential errors. Additionally, integrating various data sources like satellite imagery, drone data, and ground sensors is complex due to spatial resolution, temporal frequency, and data quality differences. Lastly, the absence of standardized evaluation metrics and protocols across studies makes it challenging to compare the performance of different models, impeding progress in establishing universally effective fire detection systems.

5. Conclusions

An extensive analysis of fire detection using deep learning (FDDL) literature from 1990 to 2023 indicates a notable increase in research activity, particularly since 2010, emphasizing the growing significance and practical applicability of FDDL technologies. This upsurge, and identifying significant trends in publication output, influential journals, collaborative research endeavors, and thematic focus areas provide valuable insights into the field's development. Our findings underscore the necessity for continual advancements in computational power and remote sensing technologies to improve fire detection capabilities. As these technologies advance, the field shows promising potential for further expansion and refinement, especially in addressing the intricate challenges posed by wildfires.

This review highlights crucial opportunities for future research, including integrating advanced deep learning techniques with state-of-the-art remote sensing technologies. This integration can potentially enhance the development of more efficient and accurate fire detection systems, facilitating timely response and mitigation efforts. Promising avenues for future exploration include innovations such as using generative adversarial networks (GANs) for data augmentation and developing hybrid models that combine detection, classification, and segmentation tasks. Additionally, fostering interdisciplinary collaborations involving environmental science, computer science, and engineering experts can lead to comprehensive solutions that seamlessly integrate deep learning with computational and ecological expertise.

In addition, the growing trend of international collaboration has been instrumental in fostering innovation and knowledge exchange in FDDL research. Countries like China, the United States, Brazil, and Australia have played significant roles in advancing the field, demonstrating the global impact of these efforts. As the field progresses, interdisciplinary and international collaboration will remain crucial for overcoming the current limitations, such as the need for large and diverse datasets, real-time detection, and model generalization across various environmental conditions.

A promising avenue for further FDDL research in the foreseeable future involves leveraging edge computing to enable on-site fire detection. By deploying deep learning models on decentralized devices like drones, cameras, and sensors, researchers can conduct the real-time analysis of local environmental conditions and identify potential fire incidents directly at the source. This approach can significantly enhance response times and fire management strategies. Overall, the ongoing refinement of deep learning models, advanced computational methods, and cross-disciplinary collaboration are crucial for developing reliable, scalable fire detection systems that protect lives, ecosystems, and infrastructure from the devastating impacts of wildfires.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/land13101696/s1, Table S1: The table provides details on the 66 most influential publications selected for this study on forest fire detection using deep learning in remote sensing. Refs. [36–101] are cited in the Supplementary Materials.

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