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Overhead Transmission Line Fragility, Climate-Induced Risks and Geospatial Artificial Intelligence: A Systematic Bibliometric Review

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ABSTRACT

This paper presents a systematic bibliometric and structured review of research on overhead transmission lines (OTLs), focusing on fault and outage driven by climatic and environmental variables. The paper examines the evolution of OTLs fragility studies in conjunction with the application of artificial intelligence (AI), machine learning (ML), deep learning (DL), and geospatial techniques for power-system resilience assessment. Global research trends, thematic evolution, and international collaborations related to climate-induced risks are examined, and existing OTLs fragility, AI-based, and climate adaptation frameworks are synthesised. The analysis reveals a strong dominance of AI, fault diagnosis, and power-system engineering themes, with limited integration of climate, environmental, and geoscience perspectives, despite moderate growth since 2022. Quantitative analysis confirms weak coupling between AI and environmental research, while OTLs vulnerability studies remain event specific and fragmented. Significant regional imbalances are identified, with African contexts underrepresented. Overall, the literature remains fragmented, with no comprehensive end-to-end geospatial artificial intelligence (Geo-AI) frameworks adequately addressing the cumulative multi-hazard impacts of climate and environmental variables on OTLs reliability. Data used for analysis are sourced from Web of

Science, Scopus, and IEEE Xplore to identify leading contributors and methodologies for modelling and quantifying power system resilience.

Keywords

Climate change; Environmental monitoring; Geosciences; Geospatial artificial intelligence (Geo-AI); Machine learning; Artificial intelligence; Overhead transmission lines

1. Introduction

Globally, nations are experiencing unprecedented losses of human life, infrastructure, and economic assets as a result of disasters driven by climate variability and intensifying extreme weather events (IPCC AR6, 2021, Behera, 2024). The convergence of record-breaking heat, ocean warming, and rising sea levels fundamentally reshapes the hazard landscape for critical infrastructure such as overhead powerlines (Braneon et al., 2024, AghaKouchak et al., 2020, Vitousek et al., 2023). These phenomena are transboundary and nonlinear, disproportionately affecting developing countries with limited institutional and financial adaptive capacities (Harris et al., 2023). Climate change-driven extreme weather events produce compounding stresses on overhead line systems, exacerbating infrastructure degradation and contributing to elevated outage frequency and duration, widespread blackouts, and considerable economic losses (Gonçalves et al., 2024). Beyond routine maintenance, these trends are imposing escalating challenges to energy security, underscoring an urgent need for climate-resilient power system planning, including infrastructure hardening, adaptive operations, robust risk assessment, and the integration of climate projections into system design and policy.

The European Network of Transmission System Operators for Electricity (ENTSO-E) positions itself as playing a pivotal role in enabling a climate-neutral Europe by 2050 (Ciapessoni et al., 2015, Fritsche et al., 2021), as stated across its strategic and statutory publications. Their operational reporting for 2024 explicitly identifies extreme meteorological conditions as a risk factor for power system operation, adequacy, and documented weather-linked incidents within its incident statistics (Electricity and (ENTSO-E);, 2025).

The United States (US) similarly shows patterns of vulnerability consistent with other regions, as highlighted in the literature and United Nations (UN) reports (United Nations Development Programme (UNDP). Bureau for Crisis Prevention, 2004). In response to escalating climate risks,

the US is increasingly adopting automation. Machine learning (ML) and artificial intelligence (AI) enabled solution systems are being deployed to strengthen utility operations (Cabrera-Tobar et al., 2023, Petit et al., 2022, Stanković et al., 2022).

Recent extreme events in China highlight both the growing vulnerability of energy infrastructure to climate hazards and the increasing effectiveness of technology-enabled disaster risk reduction. Super Typhoon Yagi (2024) resulted in severe electricity supply disruptions, particularly in Hainan Province, as indicated by satellite imagery, power outages and overhead power lines network damage assessments. The findings of the analysis and assessments indicate limited resilience and coping capacity, as over 80% of urban electricity distribution networks experienced temporary failures (Wang et al., 2025, Yang et al., 2022, Li et al., 2025b, Li et al., 2025a). In contrast, the response to Typhoon Ragasa in late 2025 reflected a more anticipatory, technology-driven approach to disaster preparedness (Tsai et al., 2026). Large-scale pre-emptive evacuations demonstrated the practical value of UN and World Meteorological Organization (WMO) guidance advocating AI and ML enabled forecasting and geospatial decision-support systems (DSS) (UNISDR, 2015, Lei et al., 2024, Wang et al., 2025, LeComte, 2026, Kandiah et al., 2025).

Organisations such as the Electric Power Research Institute (EPRI) and the International Council on Large Electric Systems (CIGRE) have sponsored and published technical papers to help power utilities anticipate, withstand, and recover from extreme weather and climate-induced disruptions. EPRI technical report indicated that the use of hybrid weather modelling with geospatial science will help address the costly losses from extreme weather and climate events. EPRI has developed advanced, utility-scale climate risk assessment frameworks, that integrate hybrid weather modelling, geospatial science, and visual analytics to support utility-level climate risk assessment (EPRI, 2025b, EPRI, 2022).

Energy demand in Sub-Saharan African countries is expected to triple as population and urbanisation increase, and as more people move to cities, gaining easier access to electricity (Quarcoo et al., 2025). South Africa's population has expanded significantly, rising from 41.1 million in 2002 to an estimated 60.6 million in 2025 (Statistics South Africa, 2025), and this poses additional challenges to the nation's already-strained infrastructure. This population growth has led to high electricity demand, creating a need to manage a balance between supply and demand to avoid outages (Kwakwa and Adusah-Poku, 2019).

South African Power Utility Eskom SoC Holdings Limited owns the country's economic and strategic assets, including power stations and substations, as well as overhead lines that traverse the country. Eskom Power Utility subsidiary, National Transmission Company South Africa (NTCSA), amongst its assets, operates and maintains 33,328 km of OTLs that traverse across the country and 221 substations (Eskom Holdings SoC Limited, 2026). According to the transmission development plan (TDP) report, 14,494 km of new transmission lines and 52 substations are planned for construction between 2025 and 2034 (National Transmission Company South Africa, 2024). OTLs are inherently prone to multiple vulnerabilities stemming from network design, operational conditions, and environmental and climatic factors, which may compromise their performance and reliability (Vajeth et al., 2003, Majodina et al., 2018, Eskom Holdings SoC Limited, 2005).

The South African transmission network predominantly operates at alternating current (AC) voltage levels ranging from 132 kV to 765 kV, supplemented by a high-voltage direct current (HVDC) interconnection rated at approximately ± 550 kV, reflecting the strategic role of long-distance and cross-border power transfer within the regional grid (Minnaar et al., 2012). OTLs constitute a critical component of national power systems, serving as high-voltage infrastructure designed to convey bulk electrical energy from generation facilities to transmission substations, major industrial consumers, and distribution substations.

For over a decade, Eskom Holdings SoC Limited has faced operational challenges in fulfilling its critical mandate of ensuring an uninterrupted power supply to its customers. Several power outages result from the complex and inseparable interaction between climatic and environmental factors, particularly severe weather conditions (Majodina et al., 2018, Fan et al., 2023, Zhang, 2025). Climatic stressors such as heatwaves, droughts, extreme winds, and wild fires, when combined with environmental and anthropogenic factors including vegetation characteristics, topography, and settlement patterns, give rise to multi-hazard risk pathways that can trigger frequent outages and cause infrastructure damage (Peace and McCaw, 2024, Schweikert and Deinert, 2021). There is a broad global consensus that electricity is a critical economic resource and a key determinant of national economic growth. Consequently, damage to electricity infrastructure and electricity outages impose substantial economic costs, amounting to billions at the national scale (Vajeth et al., 2003, Glossop, 2008, Preston et al., 2016, EPRI, 2025a, EPRI, 2025b).

In this context, OTLs often exhibit suboptimal performance due to the combined effects of mechanical, technological, electrical, and environmental stressors. Importantly, OTLs performance degradation is not solely attributable to identifiable electrical causes. Investigations into OTLs fault and outage sources have revealed the existence of an unexplained class of faults and trips that significantly undermine system reliability and increases line fragility, later attributed to a combination of known and unknown environmental and climatic conditions (Bisnath et al., 2006).

To address gaps in understanding fault origins and the misclassification of climate and environment-related faults, this study aims to conduct a systematic literature review examining the application of geospatial intelligence to assess and monitor climatic and environmental impacts on overhead transmission lines, with implications for the risk and vulnerability of current and future NTCSA infrastructure.

This paper employs a bibliometric analysis to systematically examine global research on OTLs faults, identifying publication trends, thematic patterns, and research trajectories. It further synthesises existing knowledge on OTLs fragility under climatic and environmental stressors, with an emphasis on modelling approaches that integrate geospatial sciences, statistical methods, and geo-artificial intelligence (Geo-AI).

The primary aim of this study is structured around two key objectives. First, it provides a comprehensive yet concise synthesis of existing research on OTLs faults and the modelling of climatic and environmental variables, offering valuable insights for researchers and power utility practitioners. Second, it analyses the existing literature to identify research trends, thematic hotspots, and critical research gaps in OTLs fault modelling within the geoscience's domain.

The next sections present the materials and methods, including the methodology, data sources, and tools used for the bibliometric analysis. The results are presented and discussed, followed by concluding remarks that summarise the study's key findings.

2. Transmission OHL Fault and trips modelling

2.1 Introduction

Although utilities have used several technologies to detect various types of faults, these approaches have limitations that require site visual inspections to close the gaps (Abid et al., 2021). This is

especially crucial because it remains difficult to differentiate between faults and trips caused by fires, pollution-related contaminants, and bird streamers (Zhang, 2025, Xie et al., 2021, Shahpari et al., 2019, Panteli et al., 2017, Panteli and Mancarella, 2015). As outlined above, faults can be categorised into mechanical, electrical, climatological, and environmental types. This literature review will synthesise research on climatological and environmental variables alongside contemporary AI scholarship to evaluate their collective influence in precipitating electrical and mechanical faults, as well as operational trips, within OTLs systems.

2.2 Climate Hazards for overhead transmission lines

Climate describes the long-term statistical properties of weather, its averages, variability, and extremes typically assessed over multiple decades (IPCC, 2023b). Climate hazards are defined as natural or human-driven physical events or trends that can threaten human health (e.g., morbidity and mortality) and damage infrastructure and natural ecosystems (IPCC AR6, 2021). The severity of impact of a hazard depends on many factors, including the likelihood of occurrence, the degree of exposure, the vulnerabilities of populations and assets exposed, and the institution's coping capacity measures that have been implemented (Cardona et al., 2012, Birkmann et al., 2015).

EPRI has developed technical guidelines (Sutanto and Heller, 1993), focusing on climate resilience in power systems. EPRI's frameworks integrate hazard metrics with vulnerability and risk assessments, thereby outlining adaptation pathways relevant to utility planning and operations (EPRI, 2025a, EPRI, 2024, EPRI, 2025b, EPRI, 2022). The hazard-metrics framework documented by EPRI presents a generic climatic drivers and acute extremes relevant to the energy sector, organised by physical domain (EPRI, 2025a).

Climate-induced disasters and extreme weather events pose serious threats to powerline infrastructure, necessitating proactive adaptation strategies. The EPRI Climate READi report classified transmission vulnerability to climatic events into two categories: acute and chronic climatic-induced hazards. The acute events (e.g., floods, heatwaves, storms, wildfires) and chronic conditions (e.g., rising temperatures, shifting wind patterns, humidity changes). The report further highlights the necessity of conducting comprehensive hazard assessments that are integrated with geospatial analysis and mapping. It recommends that analytical outputs be classified and presented according to defined risk-zone levels to support informed and resilient decision-making for overhead OTLs systems. EPRI also advocates collaboration between utilities and academic

institutions, supported by sustained investment and targeted capacity-building programs (Smith et al., 2003, Burillo et al., 2019, Drew. M et al., 2023). Another critical factor is the de-rating associated with estimated vulnerabilities, which can be addressed by developing credible and improved models (Drew. M et al., 2023).

Historically, electric power systems have usually been designed to operate under relatively stable weather and loading conditions. However, due to outages, asset damage, and infrastructure losses, the design of new infrastructure now accounts for extreme weather events. This posture will ensure that infrastructure is resilient to climate-induced disasters and extreme weather events. OTLs are generally designed to have an operational lifespan of 40 to 60 years (Suwanasri et al., 2024). Given this extended lifespan, such infrastructure is likely to be exposed to evolving stressors over time, increasing the risk of performance degradation, reduced reliability, and a shortening of its effective operational life.

2.3 Overhead transmission lines vulnerability model

There are engineering approaches that use mathematical functions to model OTLs vulnerabilities and predict the degradation or failure of components under adverse conditions, including their intensity, duration, and frequency. The analysis results are used to determine the cause of an OTLs trip or outage and separate threats or hazards into potential physical or environmental categories. These functions are referred to as fragility curves, damage functions, or dose-response functions (Dumas et al., 2019). A study by (Panteli et al., 2017, Moradi-Sepahvand et al., 2022), expanded fragility model presented by (Dumas et al., 2019) study and develop fragility models for individual towers and lines to calculate their failure probabilities based on real-time weather intensity and spatial movement. The models were integrated with probabilistic simulations to quantify the rate at which severe weather degrades network performance, using both infrastructure and operational indices. The study by (Moradi-Sepahvand et al., 2022), integrated fragility curve with Monte Carlo simulations to identify vulnerable infrastructure and evaluate potential failure scenarios during high-risk weather events. Fragility curves and damage functions, in contrast, reveal the likelihood of a system or component failure in response to a single climatic extreme event. For example, a fragility curve might answer the question “What percentage of transmission poles will fail as a function of one-minute sustained wind speed?” (Gonçalves et al., 2024).

There are multiple approaches to developing fragility curves, which can be classified into four types; judgmental, empirical, analytical, and hybrid. Judgmental approaches are based on expert opinion or engineering judgment. Empirical approaches are based on observations. Analytical approaches are based on models. Hybrid approaches combine two or more of the other approaches. Each approach will yield a different level of accuracy. The choice of approach involves making a trade-off between cost and precision that is appropriate to the application (Dumas et al., 2019, Schultz et al., 2010).

2.4 Artificial intelligence framework and models

AI frameworks are generally classified into traditional and modern approaches. Traditional frameworks are largely static and suited to structured datasets, whereas modern frameworks employ ML and DL techniques that support adaptive learning and integration with complex AI architectures. Integrating climatic variables with transmission fault data poses significant analytical challenges due to the dataset's scale and complexity. Various researchers noted that traditional methods struggle with large-scale datasets, while modern machine learning offers scalable, pattern-driven solutions that transform raw data into actionable insights (Dikshit et al., 2024, Forouheshfar et al., 2025).

In 2024, South Africa's Department of Communications and Digital Technologies (DCDT) issued an Artificial Intelligence Policy Framework to provide high-level direction and shape future policy and regulation (DCDT, 2024). The DCDT AI policy establishes expectations for developers to realise AI's potential responsibly by addressing ethical, social, and economic impacts, ensuring benefits are broadly shared and risks are effectively managed (DCDT, 2024). Globally, countries and AI users are concerned about the use of AI and their ethical boundaries, SA is also equally concerned (Zhao et al., 2024, DCDT, 2024). Therefore, the policy framework seeks to set clear guardrails, design AI ethically, protect privacy and personal data and secure systems against cyber risks.

The prevalence of data-driven methodologies has grown markedly across industries, with techniques such as ML and multivariate statistics for multi-hazard and multi-risk assessment. In response to security and ethical concerns surrounding AI, research efforts have increasingly emphasised the development of robust system architectures that mitigate adversarial and backdoor

attacks while promoting federated learning (FL), uncertainty quantification, and explainability (Miyaji et al., 2026, Xu et al., 2023, Madry et al., 2017).

The complex relationships among vulnerability, hazard, and risk factors require integrating large, multidisciplinary datasets. The rising frequency and complexity of climate-induced hazards have driven demand for systems that are transparent, interpretable, and capable of delivering timely, adaptive responses. In this context, ML, AI systems and multivariate statistics are identified as the best methods for providing accurate results (Forouheshfar et al., 2025, Diehr et al., 2025, Ferrario et al., 2025). A recent study by (Dikshit and Alipour, 2025) demonstrated the effectiveness of a hybrid modelling approach for analysing OTLs faults in relation to environmental variables. The study developed a probabilistic framework integrated with a Monte Carlo simulation-based DSS to capture uncertainty and assess fault likelihood under varying environmental conditions.

A growing body of research has explored the application of Convolutional Neural Networks (CNNs) to image-based classification and climate disaster risk analysis. CNNs excel at extracting spatial features from satellite imagery, enhancing hazard prediction and environmental monitoring. The field has advanced with hybrid deep learning models like CNN-RNNs, U-Net, SegNet, and CNN-LSTM-XGBoost (Janga et al., 2023, Saleem et al., 2025, Reichstein et al., 2019). These frameworks enable robust spatio-temporal modelling of complex system dynamics. They improve the prediction, detection, and mitigation of climate-driven disaster risks, and reflect a shift toward intelligent, data-driven climate resilience and disaster management (Ferrario et al., 2025, Diehr et al., 2025, Padmaja et al., 2025, Saleem et al., 2025). The rise in the development of the digital twin (DT) framework has attracted attention from power utility owners, mainly because of its ability to model and simulate real-world environments. The study by (Wang et al., 2024) explored DT and created high-fidelity virtual models that mirror physical network components. DT has a unique ability to bridge the gap between static mathematical theories and the unpredictable realities of live data transmission, as it accurately models and simulates faults signal.

3. Systematic review analysis

3.1 Analysis methodology

The method enables researchers to identify and retrieve information at global or local scales. The intention is to comprehensively address the research questions, previous studies, and support

evidence-based decision-making (Siddaway et al., 2019). The method benefit researchers by enabling transparent conduct, reduce bias, thus providing more reliable findings from which conclusions can be made (Munn et al., 2018, Cumpston et al., 2019).

There have been studies conducted by various researchers in the field of powerline faults, appreciation of modern technology, such as the deployment of geospatial science, artificial intelligence tools, has been lacking. To understand the extent of integration across this multidisciplinary field, and to avoid missing important literature, a bibliometric analysis will be conducted to highlight and reveal recent and other relevant studies. The systematic review seeks to reveal the most used keywords that form a network across geoscience and over-the-headline literature integrated with modern technologies.

The study will employ a systematic review to synthesise the literature on environmental and climatic variables that pose risks to transmission power line operations, leading to fault trips and outages. This study will employ established systematic review methods, with reporting guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Page et al., 2021). The PRISMA guideline provides a simplified method for researchers to address critical questions through five stages to determine whether to proceed with the study, (1) data search strategy, (2) data collection, (3) quality check and quality control, (4) quantitative and qualitative analysis (5) results interpretation (Page et al., 2021), see Figure 1.

The analysis is conducted across various journals, papers, and documents published paper between 2004 and 2026 with a focus on (1) an understanding of annual publication trends, (2) research the publication's global geographic distribution, (3) analyses the relationship between authors through co-authorship analysis, (4) highlight the co-citations between the authors globally and (5) trending words and key-occurrence analysis from secondary database.

3.2 Search strategy

Bibliometric information will be obtained from science-rich databases Web of Science (WoS) and Elsevier Scopus (Muñoz-Alegría et al., 2025, Jurgilevich et al., 2017, Forouheshfar et al., 2025) to extract various information using statistical and bibliometric methods.

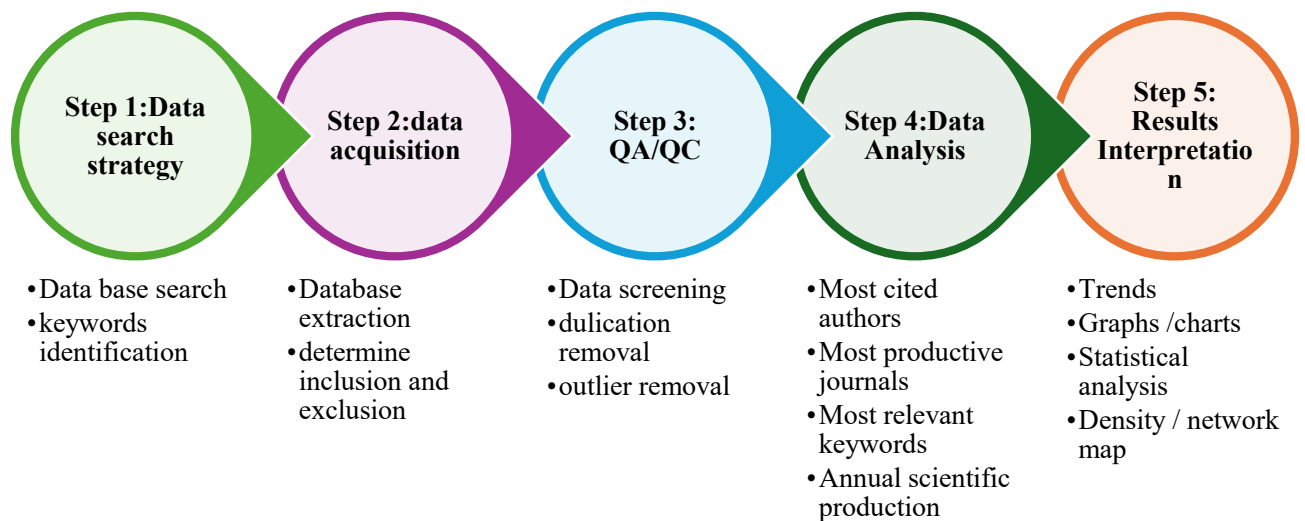


Figure 1: PRISM workflow

This systematic review adheres to rigorous bibliometric standards to assess the reproducibility and validity of the analysed dataset (Munn et al., 2018). To ensure quality standards, a comprehensive literature search was conducted across three academically, scientifically and engineering-approved databases (WoS, Elsevier Scopus, IEEE, and Dimensions). The study limited the data collection to peer-reviewed publications and technical reports released between January 2004 and 2026. The search strategy uses a combination of keywords related to transmission overhead lines, climatic variables, environmental variables, meteorological hazards, resilience, risk, vulnerability and Artificial intelligence. Upon initial assessment of three databases, the Dimensions database yielded 38 records with poor metadata and was therefore discarded from the study. The review will use the WoS and Elsevier Scopus databases as primary sources, as they cover a range of multidisciplinary topics. Although IEEE yielded 49,338.00, only 250 records were downloaded to serve as secondary literature for validating quality and citations, addressing gaps in engineering-based literature, geoscience, and AI information availability. IEEE Xplore imposes batch-download limits on record retrieval, often restricting users to small subsets at a time, thereby reducing efficiency for large-scale database downloads.

3.3 Data acquisition and workflow

The specific Boolean search strings utilised below are to extract information from Scopus (Elsevier), SoW and IEEE Xplore. Date of last search: 20 March 2026.

(ALL (("transmission line" OR "transmission system" OR "overhead line" OR "overhead transmission line" OR "OHL") AND ("fault" OR "failure" OR "outage" OR "blackout" OR "forced outage" OR "trip")) AND ALL ("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "ML" OR "DL") AND ALL ("GIS" OR "spatial" OR "mapping" OR "remote sensing" OR "geospatial science" OR "geography" OR "climatic" OR "climate change" OR "environmental")). The database information extraction process ensured the dataset analysed was topically relevant. Consequently, studies were filtered based on the strict inclusion and exclusion criteria defined below, adhering to (Page et al., 2021) PRISM guidelines:

1. **Relevance:** The scope was strictly limited to studies focusing on high-voltage transmission systems, environmental and climatic-induced faults, trips and geoscience modelling and AI. Papers that solely addressed low-voltage distribution faults were excluded.
2. **Impact Threshold:** A pre-specified impact-magnitude threshold determined inclusion. We focused on studies addressing hazards to OTLs (environmental, climate-related and extreme weather) and on evaluations of advanced technologies (geospatial analytics, artificial intelligence, data-driven models) used to detect, forecast, or mitigate OTLs faults under adverse environmental conditions.
3. **Data Quality:** Sources lacking verifiable quantitative data regarding the date, location, or impact magnitude were excluded from the analysis. The SoW and Scopus datasets were combined to ensure a broad range of scientific results. The data was processed to remove duplicates prior to analysis. Then, the defined filters were applied. Thus, a final dataset was established for bibliometric analysis.

3.4 Bibliometric and science mapping tools

This study was conducted using bibliographic data retrieved from the WoS and Scopus (Elsevier) databases. Data analysis and visualisation were performed using R-Statistics (Bibliometrix and Biblioshiny), VOSviewer, and Microsoft Excel. The bibliometric analysis presents results by the categories outlined below.

The bibliometric analysis presented the results as follows.

- Trends tables and map
- Graphs /charts
- Statistical analysis
- Density/network map

4. Analysis Results

Primary database results analysis

The bibliometric analysis was based on an integrated dataset retrieved from the Scopus and WoS databases. The combination of the two leading citation databases ensured comprehensive coverage of the literature and strengthened the robustness of the analysis, which is particularly important given the presented complexity and multidisciplinary nature of the research domain. To retrieve relevant material, we applied limitations using published year, theme, language, article type and keywords. Initially, we identified a total of 2742 records across the two databases, with 742 from Web of Science and 2000 from Scopus. After eliminating 61 duplicate entries, we were left with 2681 records for bibliometric analysis.

Table 1 represent the database summary, after merging the Scopus and WoS databases and cleaning up the database, the bibliometric analysis results were performed. A total of 4,012 unique authors contributed to the study corpus. Among these, 1,931 authors produced single-authored documents, resulting in 1,951 single-authored publications, while 5,274 author appearances were associated with co-authored works. These figures indicate a mixed authorship structure characterised by both individual scholarship and collaborative research. On average, each document was authored by approximately 2.49 authors, with an average of 1.97 co-authors per document, indicating moderate collaboration intensity. The documents per author ratio of 0.67 suggests a dispersed authorship pattern, typical of emerging or interdisciplinary research fields in which many contributors publish a limited number of papers. The proportion of internationally co-authored publications was 6.19%, indicating that while collaboration is present, research activity remains predominantly domestic or regionally

focused. Nevertheless, the calculated collaboration index of 2.71 confirms that a substantial share of research output is produced through collaborative efforts.

The bibliometric analysis summary results highlighted a rapidly growing, conceptually diverse research field characterised by strong growth in recent years, moderate citation impact, and a balance between single-authored and collaborative publications. Although collaborative research is evident, the low proportion of international co-authored publications suggests constrained global integration, implying a degree of body-of-knowledge islanding concentrated within developed countries.

Metadata information

Table 1 presents an illustration of two merged databases covering the period 2004–2026, highlighting core bibliometric attributes such as document types, publication outlets, authorship profiles, and the structure of co-authorship collaboration networks. The analysis was guided by the R statistical environment and bibliometric methods implemented through the bibliometrix package, as proposed by (81)

Table 1: Main information about the data

Description	Results
Timespan	2004 - 2026
Sources (Journals, Books, etc)	755
Documents	2681
Annual Growth Rate %	19.66
Document Average Age	2.05
Average citations per doc	8.988
Average citations per year per doc (rate)	2.448
References	1
DOCUMENT TYPES	
Article	2614
Article; book chapter	2
Article; data paper	1
Article; early access	10
Article; proceedings paper	9

Article; retracted publication	2
Book	43
DOCUMENT CONTENTS	
Keywords Plus (ID)	13288
Author's Keywords (DE)	9387
AUTHORS	
Authors	4012
Author Appearances	5274
Authors of single-authored docs	1931
AUTHORS COLLABORATION	
Single-authored docs	1951
Documents per Author (ratio)	0.668
Co-Authors per Doc (ratio)	1.97
International co-authorships %	6.192

4.1 Annual scientific publication trend

The annual scientific growth distribution reveals a long period of negligible activity (2004–2018), followed by modest expansion (2019–2021) and a pronounced acceleration beginning in 2022. The field reaches peak output in 2024–2025, a phenomenon indicating intense global interest and rapid methodological or technological advancement. The year 2026 shows early signs of growth and is already above 2023 levels, as illustrated in **Figure 2**. The analysis was guided by the R statistical environment, employing bibliometric methods through the bibliometrix package by (Aria and Cuccurullo, 2017).

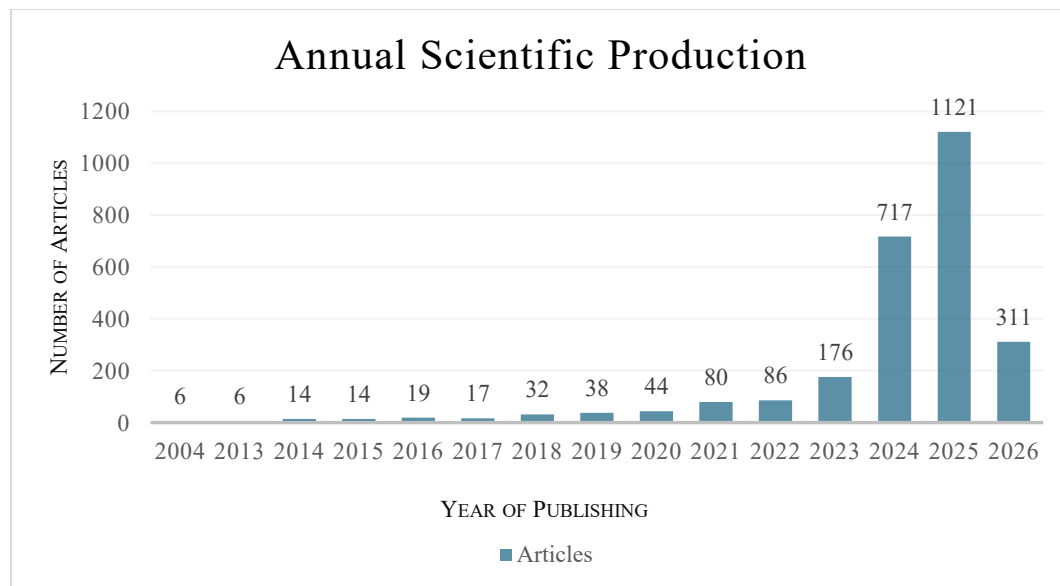


Figure 2: Annual scientific literature growth

4.2 Geographic global research distribution

Figure 3 represent global collaboration analysis revealing a highly centralised international research network characterised by asymmetric collaboration patterns. China emerges as the primary hub for collaboration, maintaining strong bilateral links with leading research economies such as the United States and the United Kingdom, as well as with other regional partners. The analysis presents the United States as a secondary global connector with a more distributed collaboration profile. The absence of collaboration involving African countries suggests constrained participation in the global network, highlighting potential deficits in cross-regional knowledge transfer and international relational capacity. The map was prepared using biblioshiny as proposed by (Aria and Cuccurullo, 2026)

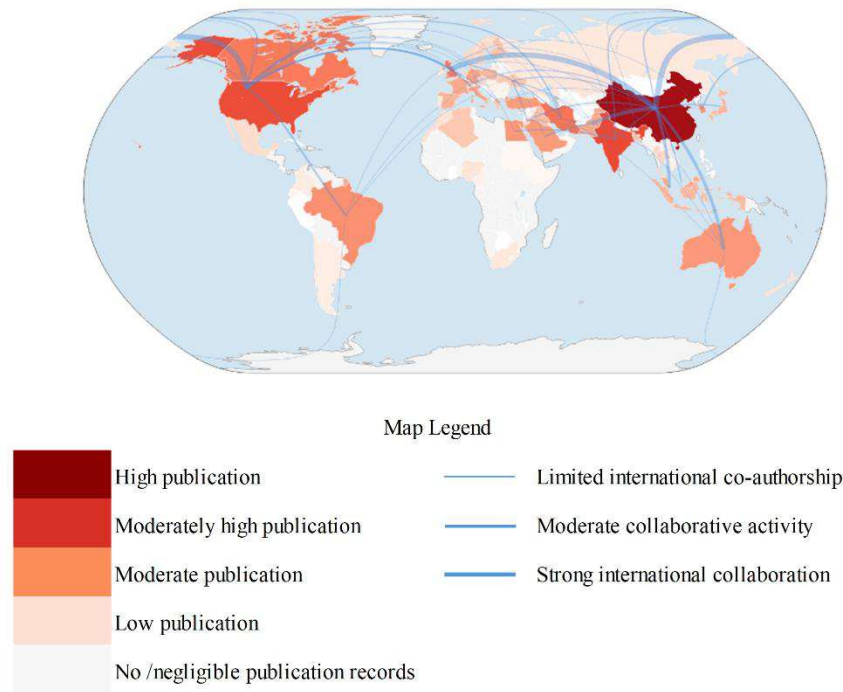


Figure 3: literature global distribution

Source (Aria and Cuccurullo, 2026)

Network density

$$\text{density} = \frac{E}{N(N-1)/2} \quad \dots\dots\dots \text{Equation 1: Network density equation}$$

1. E - represents the number of observed edges (links) in the network.
2. N - denotes the number of nodes (e.g., authors, institutions, or countries).

Consistent with PRISMA-reporting guidance (Page et al., 2021), network density as per *Equation 1* was used as a descriptive metric to map international collaboration by assessing the proportion of observed country-to-country connections relative to all possible connections within the dataset.

4.3 Most Productive Authors

Table 2 represent the most productive authors in the global literature, indicating that Wang Y is the most prolific contributor with a total of 29 publications. When author productivity is assessed

using fractionalised counting, which accounts for co-authorship and provides a contribution-adjusted measure, Wang Y and Liu Y remain the leading contributors, each exceeding a fractionalised publication threshold of five. The analysis also reveals a predominance of East Asian author names, which aligns with the global collaboration network findings that identify China as the primary leading contributor in the field. The analysis was performed using R statistical software, employing the bibliometrix package to conduct quantitative bibliometric and science mapping analysis (Aria and Cuccurullo, 2017).

Table 2: The 20 most productive authors are ordered by the number of publications in the field

No Authors	Authors	Articles	Authors	Articles Fractionalized
1	Wang Y	29	Wang Y Kuznetsov B N T B I C K K V	5.61
2	Liu Y	19	K B	5
3	Li Y	16	Liu Y	4.21
4	Li Z	16	Li Y	4.15
5	Wang J	16	Łuczak D	4
6	Zhang Y	15	Wang J	3.98
7	Liu J	14	Zhang Y	3.58
8	Zhang Z	14	Liu J	3.45
9	Li J	13	Li Z	3.25
10	Liu C	12	Li L	3.19
11	Li L	11	Wang L	3
12	Li Q	11	Farshad M	3
13	Wang X	11	Wang X	2.59
14	Wang Z	11	Li J	2.32
15	Zhang H	11	Liu C	2.29
16	Chen J	10	Wang Z	2.25
17	Wang H	10	Zhang Z	2.22
18	Wang L	10	Zhang H	2.21
19	Zhang W	10	Dehghanian P	2
20	Liu H	9	Elsayed E Y M S A	2

4.4 Bradford Law analysis of most prominent authors

Figure 4a illustrates Bradford's Law of scattering results, which was applied to descriptively map the distribution of publications across journals with a return of 757 records. The literature was partitioned into three Bradford zones with approximately equal article output but an increasing number of sources. Zone 1 (the core) comprises 20 journals producing 905 articles (33.8% of the total), Zone 2 includes 108 journals contributing 892 articles (33%), and Zone 3 consists of 629 journals publishing 884 articles (33.3%). The estimated Bradford multiplier ($b \approx 5.6$) indicates a highly concentrated core accompanied by a large, long tail of peripheral journals. The descriptive distribution pattern is consistent with Bradford's Law ($p = 0.0736$), with the non-significant p-value (≥ 0.05) indicating no meaningful departure from the theoretical model. **Figure 4b** Bradford Zone Summary graph supports the observations presented in Figure 4a, demonstrating a consistent distribution of approximately 30–35% of articles across each Bradford zone. The graph illustrates a consistent distribution of articles across the Bradford zones, providing strong empirical support for the Bradfordian model of exponential scattering and confirming a well-structured and mature scholarly domain (Aria and Cuccurullo, 2026).

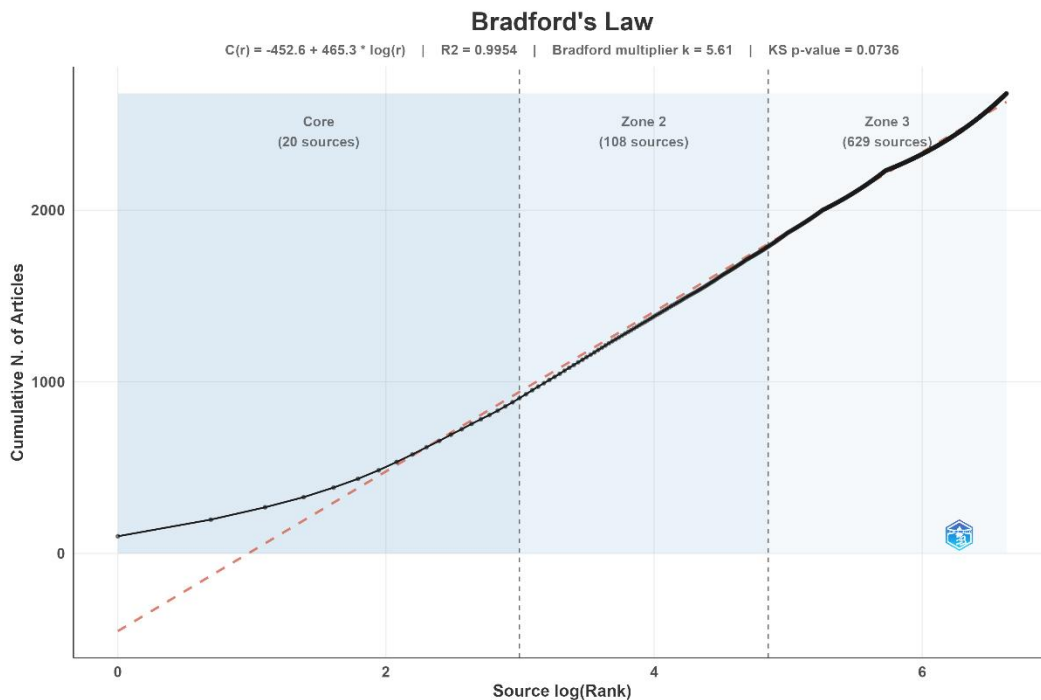


Figure 4a: Bradford law plot

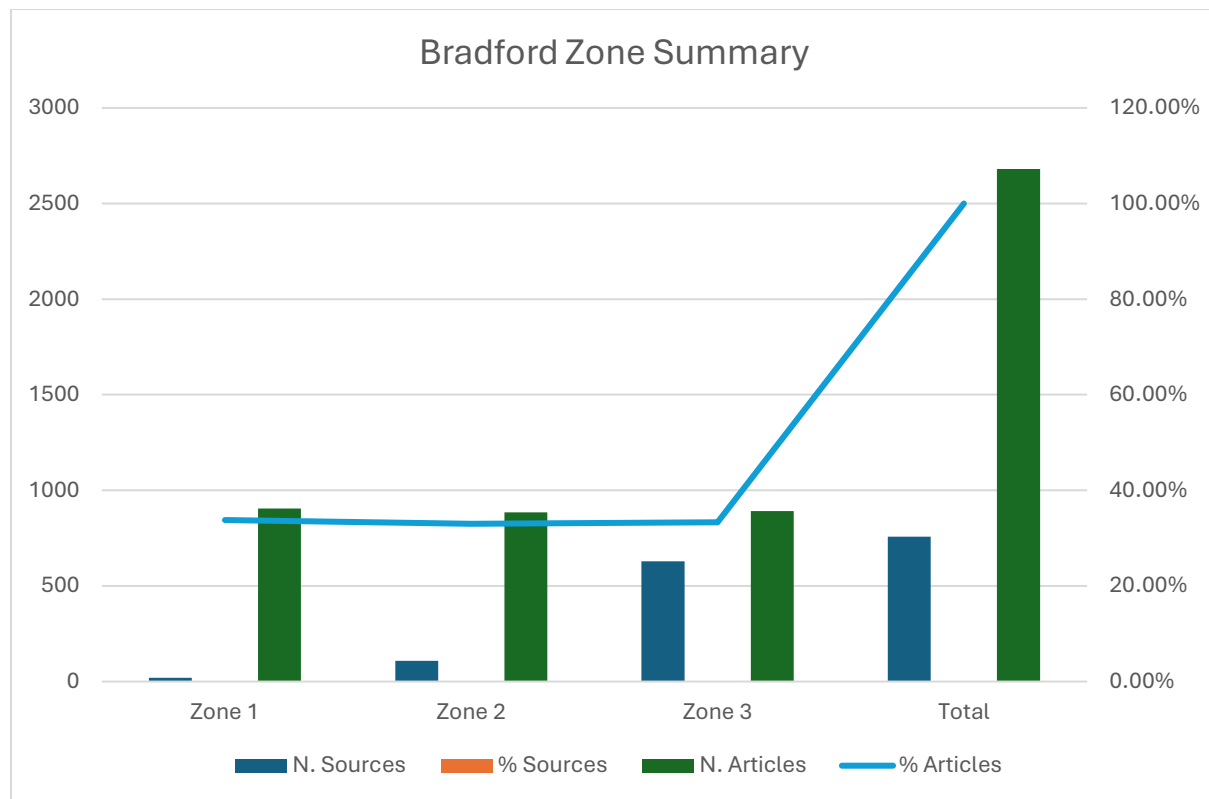


Figure 4b: Bradford Law zone summary

4.5 Co-Authorship Analysis

Figure 5 illustrates that the Fruchterman–Reingold algorithm was employed to analyse the co-authorship network, revealing several cohesive collaboration communities. After removing isolates and focusing on the largest connected component using R-Statistics (Aria and Cuccurullo, 2026). The layout shows a dense core with multiple color coded clusters, indicating frequent intra-cluster collaborations and a few bridging authors connecting communities. Thresholding edges to ≥ 2 co-authored papers reduces incidental links and highlights stable partnerships. The results demonstrate a structured and moderately centralised collaboration pattern characterised by distinct clusters and a prominent central hub. The node representing Wang Y occupies a dominant position, as evidenced by the highest betweenness centrality (189.33) reported in Table 3, indicating a strong bridging role between clusters and significant influence on knowledge flow. Additional authors, including Liu Y and Li Z, further enhance inter-cluster connectivity, reinforcing the overall network. The analysis results employed a quantitative bibliometric and systematic analysis approach as proposed by (Aria and Cuccurullo, 2026).

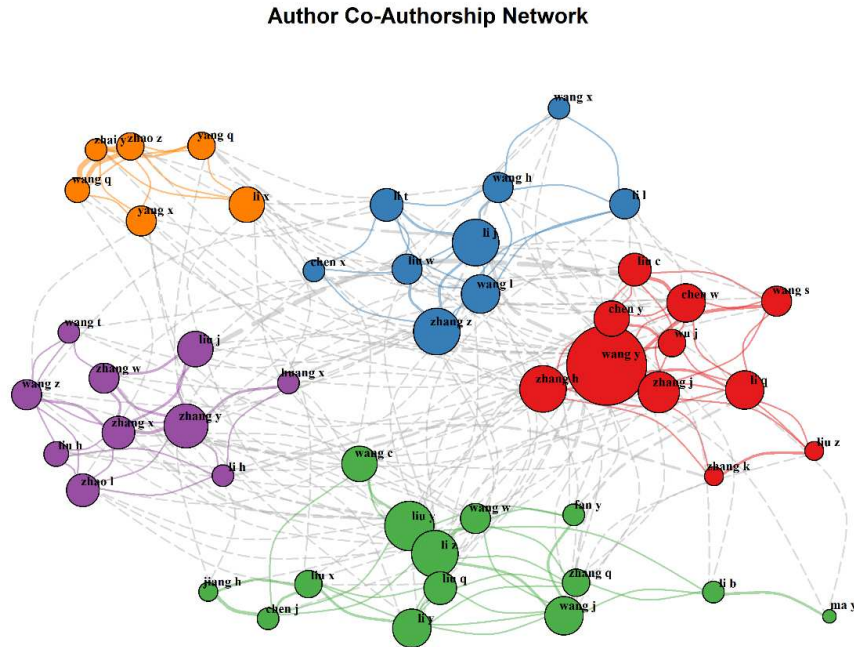


Figure 5 The Fruchterman–Reingold algorithm: Analysis of the Author Co-Authorship Network

4.6 Co-Citation Analysis

The information in **Table 3** represents co-citation analysis results, which reveal a multi-cluster collaboration structure characterised by two closely interconnected groups and a prominent central hub with strong cross-cluster connectivity. The network is highly influenced by Wang Y, who exhibits the highest betweenness centrality (189.33) and PageRank (0.0567), indicating a critical bridging role and substantial structural influence. In addition, Liu Y, Li Z, and Li Y demonstrate notable intermediary positions, particularly within the secondary cluster, reflecting their role in linking sub-networks. Cluster 1 represents the dominant core of collaboration, Cluster 2 forms a cohesive yet interconnected subgroup rather than an isolated structure. The findings highlight a structured intellectual landscape in which a small number of highly central authors act as key anchors, integrating multiple strands of the literature and promoting cohesion within the research domain. The study employed the Biblioshiny methodological framework proposed by (Aria and Cuccurullo, 2026).

For a node v , betweenness centrality is calculated as:

$$C_B(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}}$$

σ_{st} = number of shortest paths between nodes s and t

$\sigma_{st}(v)$ = number of those paths that pass through the node v

Table 3: Co-citation analysis table

Node	Cluster	Betweenness	Closeness	PageRank
Wang y	1	189.3261358	0.013888889	0.056658843
Wang j	1	24.47888686	0.011764706	0.024112119
Li l	1	15.69681792	0.010204082	0.017090978
Li q	1	12.798345	0.010869565	0.01890432
Wang x	1	8.876378316	0.010416667	0.012070331
Zhang h	1	38.18283922	0.012048193	0.028916994
Wang s	1	26.67739889	0.011235955	0.022484707
Zhang j	1	25.94306966	0.011627907	0.024975396
Zhang k	1	4.198917749	0.009803922	0.010585908
Chen w	1	12.83588926	0.011764706	0.021480225
Chen y	1	20.85431415	0.011494253	0.017981527
Li b	1	2.826015027	0.00990099	0.010415359
Yang y	1	2.854104732	0.010526316	0.011520763
Dehghanian p	1	0.733333333	0.008547009	0.009060866
Liu y	2	68.40820022	0.012195122	0.034197396
Li y	2	40.91467358	0.012048193	0.023803059
Li z	2	46.98237927	0.0125	0.032253248
Chen j	2	19.73769293	0.010752688	0.021081981
Liu h	2	8.984165901	0.010416667	0.01358814
Li h	2	11.43977284	0.01010101	0.015799674

4.7 Keyword Thematic Map

Figure 6 represent yearly trending themes analysis, demonstrating significant shifts in research focus across the study period. Early studies (2014–2018) were dominated by traditional power system topics such as field or field maintenance, TCSC, fault resistance, and power transmission reliability. This was followed by a transitional phase (2018–2022) characterised by the growing use of computational approaches, including models, neural networks, artificial intelligence, and simulation. In recent years (2022–2026), research has increasingly focused on advanced data-driven techniques, particularly deep learning, machine learning, fault detection, and fault diagnosis, with a significant number of studies on these topics.

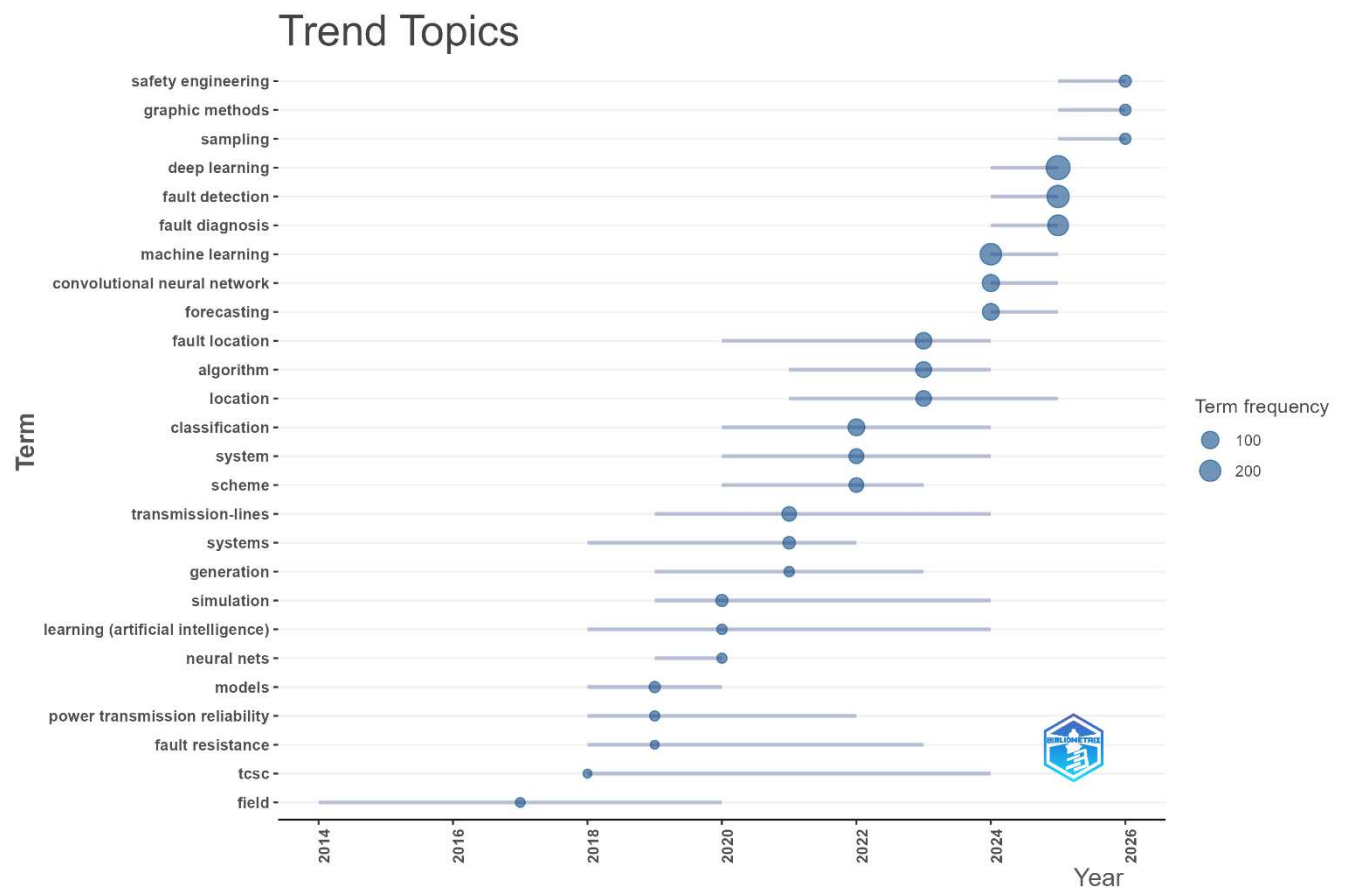


Figure 6: Yearly top trending topics

Notably, deep learning and artificial intelligence are gaining prominence, indicating the accelerating adoption of advanced computational techniques for OTLs fault detection and reliability assessment. The overall research trajectory points toward AI-driven, network-aware, and

vision-enabled reliability analytics, signalling both methodological maturation and expanded operational deployment. This thematic analysis was conducted using Biblioshiny, ensuring transparent and reproducible mapping of the field’s conceptual landscape (Aria and Cuccurullo, 2026).

5. The Institute of Electrical and Electronics Engineers (IEEE) Xplore

5.1 Secondary database results analysis

In accordance with PRISMA-ScR reporting of information sources, the IEEE Xplore database was included as a secondary source to support validation of the bibliometric analysis conducted using the primary database. The information extraction is as per the keywords used in Scopus and WoS databases. The IEEE Xplore RIS dataset was analysed using VOSviewer to examine the evolution of research and to identify current thematic trends in OTLs fault detection and reliability assessment.

5.2 IEEE maturing and emerging

Table 4 represent IEEE trending words present the thematic evolution analysis, highlighting that classification, classifier, and classification accuracy represent the mature core of the field, as evidenced by their high total link strength (TLS), occurrence frequency, and their role as foundational topics prior to 2021. Assessment and change detection are consolidated research themes, reaching peak prominence during 2021-2022 and serving as key components of contemporary analytical workflows. More recently, AI models and techniques, automation, and cloud-based technologies have emerged as major innovation drivers, reflecting a shift toward scalable and operationally oriented solutions between 2023 and 2024. Emerging themes for 2025 include autonomous systems, building management systems (BMS), and catalogue-related concepts, highlighting growing attention to deployment, energy management, and data governance. Additionally, AD diagnosis appears as a specialised application area, indicating the growing adoption of these technologies in domain-specific contexts.

Table 4: IEEE trending words

Status	Strong signals	Why
Mature core	classification, classifier, classification accuracy	Highest TLS/occ; pre-2021 anchors

Status	Strong signals	Why
Consolidated methods	assessment, change detection	2021–2022 peaks; structure today's pipelines
Emerging engines	AI model/technique, automation, cloud	2023–2024 surge; platform & ops orientation
Frontier	autonomous system, BMS (energy), catalogue	2025 recency; deployment, energy, governance/curation
Specialised apps	ad diagnosis	2024; domain-specific adoption

Figure 7 represents the bibliometric network in VOSviewer, highlighting keyword importance through node size and co-occurrence strength, while colour gradients represent the average publication year (2016–2026), revealing a clear temporal evolution of research themes. Early clusters (purple/blue) are dominated by foundational remote sensing and image-processing methods, which progressively transition into mid-phase (green) themes integrating machine learning and hybrid modelling approaches. The most recent clusters (yellow) reflect a shift toward AI-enabled sensing, resource-efficient modelling, and emerging applications, including satellite-based CO₂ datasets and novel environmental monitoring tasks. Notably, powerline and electricity-related themes such as power systems, outages, and prediction models appear predominantly in the green-to-yellow regions of the map, indicating rapid development since approximately 2022. IEEE results show a clear thematic evolution from traditional environmental science, AI integration, advanced sensors, and climate AI. We also observe increases in clusters 2 (2026) and 5 (2025), indicating active emerging research hotspots. Cluster 3 and 4 represent transitional applied engineering themes. Cluster 1 serves as the scientific base which this study will mainly focus on.

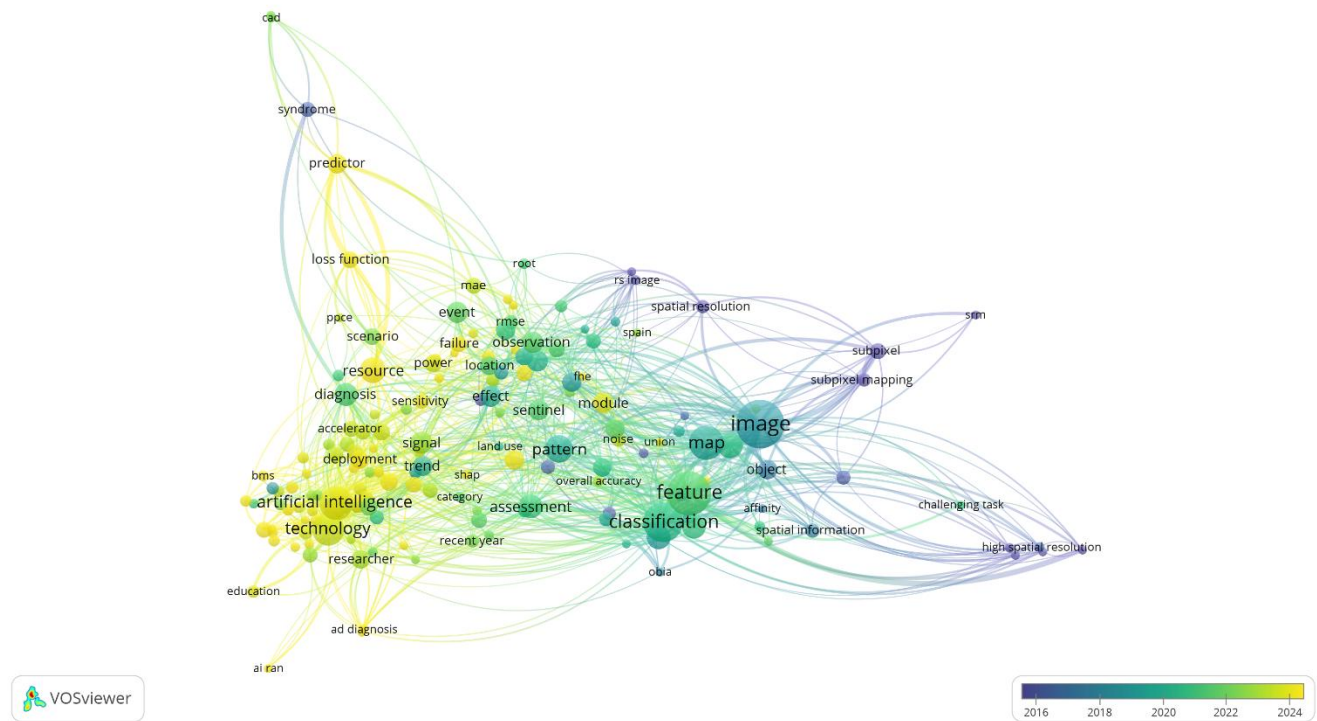


Figure 7: Keyword co-occurrence overlay map (VOSviewer).

6. Discussions

Analysis of the top-20 Most Relevant Keywords for both Author Keywords (DE) and Keywords Plus (ID) shows a strong AI/fault/ power-system signal and shows weak explicit signals on climate, environment and geoscience. This pattern mirrors the concentration of output in the most productive sources, reinforcing the earlier diagnosis of a literature gap in the limited integration of climate, environmental, and geodata with AI-driven fault analytics for OTLs. A systematic literature review corroborates this, indicating that end-to-end pipelines that fuse geoscience layers with OTLs reliability modelling remain uncommon.

To quantify the association between the key thematic areas AI, geoscience, environmental variables, climatic variables, severe weather events and OTLs. We applied a statistically reproducible method (binary tagging and year, rates/overlaps). Results show that across 2022-2026, AI-tagged publications increased by approximately 14%, while only about 20% of OTLs related studies incorporated climate, environmental, or geoscience keywords, despite annual growth of 5–6% in environmental and AI research. This pattern indicates a persistent integration

gap between AI-driven analytics and climate-environmental considerations in transmission-line reliability research. Correlation analysis over 2017- 2026 further supports this gap, showing a strong negative association between AI and environmental research ($r \approx -0.87$), in contrast to a stronger alignment between environmental and OTL-focused studies in recent years. Robustness checks using weighted and recent-window analyses confirm that coupling between environmental research and AI remains limited and has not progressed in proportion to overall AI growth.

IEEE results indicate a strong positioning between earlier remote-sensing foundations and the latest AI-deployment frontier; these themes demonstrate how electrical-infrastructure applications have become major beneficiaries of ML integration. Their strong co-occurrence with severe weather, environmental variables, failures, and resources underscores an increasing research emphasis on AI-driven grid resilience, outage prediction, and environmental risk modelling, situating OTLs research within the broader evolution toward autonomous, interpretable, and operational AI for climate and energy systems.

China's response to the 2024 and 2025 typhoons, (Tsai et al., 2026, Li et al., 2025b) demonstrates that Geo-AI-enabled DSS can play a critical role in saving lives and, to some extent, protecting physical assets. In contrast, the bibliometric analysis of both the primary and secondary databases indicates a pronounced regional imbalance, with Africa remaining underrepresented in the literature, as illustrated in Figure 3. While extensive research on AI-enabled systems for monitoring and managing critical infrastructure is evident across Western countries, East Asia, and Europe regions, comparatively limited scholarly attention has been devoted to African contexts. This finding is consistent with (Verschuur et al., 2024), who highlighted critical infrastructure hazard thresholds, especially for extreme heat and wind, and noted the persistent underrepresentation of low-income regions in related research.

The review highlighted that, while many useful vulnerability quantifications of infrastructure components are available, they are primarily empirical and single-event-driven. Additionally, environmental impacts on specific components of the electrical grid, such as underground powerlines, are understudied. Mathematical formulations that have emerged from these studies tend to describe infrastructure and end-user responses to higher ambient and extreme temperatures, low water availability, and wind and flooding from storms and heavy precipitation. Although Eskom has conducted extensive analyses of wildfire risk to OTLs, research on cascading risk

events remains limited. Insufficient attention has been given to asset maintenance under minimum and maximum extreme temperatures. During review, it became clear that there is a lack of a comprehensive assessment of cumulative damage from multiple extreme weather and climate-induced events across the various components of the electric grid. As the frequency and intensity of extreme weather and climate events are expected to rise in future, understanding the sensitivity of specific components of electricity systems and their collective vulnerability to climate and weather hazards is crucial to long-term planning. The literature highlights that high-impact, low-probability natural events significantly increase OTLs fragility, leading to faults, trips, and, in extreme cases, major outages(Rifat and Ghassemi, 2025).

NTCSA employs a routine, time-based schedule for OTLs infrastructure maintenance and inspection. However, under current climatic conditions, adherence to this interval has proven increasingly impractical. This highlights the necessity of transitioning to an impact-based maintenance framework, in which the actual or potential impact informs inspection and intervention schedules of asset failure rather than predetermined timeframes.

Despite extensive GeoAI research, hazard and risk assessment in most DSS remains fragmented across methods, scales, and sectors. Existing studies, such as those by (Moradi-Sepahvand et al., 2022, Panteli et al., 2017), suggest that multidisciplinary solutions for addressing OTLs reliability are still in the early stages of development. Therefore, the incorporation of geoscience perspectives within these studies is largely superficial, often limited to modelling extreme weather events rather than engaging with the broader geoscientific processes that influence system vulnerability.

Bibliometric analysis of the top-20 Most Relevant Keywords for both Author Keywords (DE) and Keywords Plus (ID) shows a strong AI, fault and power-system studies and explicit weakness on climate, environment, and geoscience studies. This pattern mirrors the concentration of output in the most productive sources, reinforcing the earlier diagnosis of a literature gap, which identified limited integration of climate/environmental geodata with AI-driven fault analytics for OTLs. A systematic literature review corroborates these findings, indicating that end-to-end pipelines that fuse geoscience with OTLs reliability modelling remain uncommon. The analysis results reveal that the IEEE covers electrical engineering across disciplines however, it lacks comprehensive bibliometric metadata to enable full bibliometric analysis, as with Scopus and WoS. IEEE, as a secondary source, reveal strong explicit agreement on the proposed research gap. The results

provide limited information on both climate and AI frameworks; however, the literature has documented various frameworks for studies aimed at addressing the challenge.

7. Research gaps and future research directions

Climate change has become a major driver of fragility in critical infrastructure systems, with OTLs infrastructure increasingly exposed to climatic and environmental stressors (EPRI, 2025a, EPRI, 2025b, Verschuur et al., 2024). This challenge is further exacerbated by the continued expansion of transmission networks, as reflected in the NTCSA Transmission Development Plan. Despite increasing scholarly attention, the existing literature remains constrained by limited multidisciplinary integration of AI-driven analytics with climatic, environmental, and geoscientific data. Much of the current research relies on event-specific, fragmented vulnerability assessments, which restrict broader generalizability. Furthermore, there is a persistent overreliance on single-hazard approaches and a pronounced regional bias, with African contexts significantly underrepresented. Addressing these gaps requires integrated Geo-AI frameworks for comprehensive multi-hazard OTL reliability assessment, underpinned by interdisciplinary collaboration, longitudinal analyses of cascading hazards, and operational Geo-AI DSS.

8. Conclusion

The review revealed a substantial and persistent fragmentation in the multidisciplinary integration of geoscience and remote sensing. This is a clear indication that current research remains insufficiently coordinated and fails to examine holistically how climatic and environmental variables drive faults, trips, and outages in OTLs systems. Analysis of the Scopus dataset shows that geoscience and remote sensing do not feature among the top 20 most frequent keywords, indicating limited prominence within the field's core thematic structure. Similarly, in the SoW dataset, geoscience appears only marginally, positioned near the bottom of the keyword-frequency ranking, further underscoring its weak representation. The reviewed literature indicates that no study of comparable scope and comprehensiveness has been conducted in the African context; consequently, this study offers significant value to the global research community and, in particular, to OTL utility operators in Africa.

Author Contributions

Tshisikhawe Mphaphuli: Conceptualisation, data curation, investigation, methodology, formal analysis, visualisation, and writing of the original draft.

Professor Abel Ramoelo: Supervision, conceptualisation, methodology, validation, writing, review and editing.

Professor Philemon Tsele: Supervision, conceptualisation, methodology, validation, writing, review and editing.

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Declarations

Ethics approval and consent to participate

Not applicable. This study did not involve human participants, human data, animals, or any procedures requiring ethical approval.

Consent for publication

Not applicable.

Informed consent

Not applicable. The study did not involve human participants or personal data.

Data availability

Not applicable.

Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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