

Lightning Risk Assessment: A Chronological Review of Techniques

Nur Azliza Ahmad^{1,2*}, Mohd Zainal Ab Kadir¹, Ungku Anisa Ungku Amirulddin³, Nik Norasma Che Ya⁴, Mohd Faris Ariffin⁵, Wan Azani Mustafa⁶

¹Advanced Lightning, Power and Energy Research Center (ALPER), Faculty of Engineering, Universiti Putra Malaysia (UPM), 43400 Serdang, Selangor, Malaysia

²Electrical Engineering Department, Center for Diploma Studies, Universiti Tun Hussein Onn Malaysia (UTHM), 86400 Pagoh, Johor, Malaysia

³Institute of Power Engineering, Universiti Tenaga Nasional (UNITEN), Putrajaya Campus, 43000 Kajang, Selangor, Malaysia

⁴Department of Agriculture Technology, Faculty of Agriculture, Universiti Putra Malaysia (UPM), 43400 Serdang, Selangor, Malaysia

⁵Asset Management Department, Distribution Network Division, Tenaga Nasional Berhad (TNB), 59200 Kuala Lumpur, Malaysia

⁶Faculty of Electrical Engineering Technology, UniCITI Alam Campus, Universiti Malaysia Perlis, 02100 Padang Besar, Perlis, Malaysia

HOW TO CITE:

Nur Azliza Ahmad, Mohd Zainal Ab Kadir, Ungku Anisa Ungku Amirulddin, Nik Norasma Che Ya, Mohd Faris Ariffin, Wan Azani Mustafa (2026).
Lightning Risk Assessment: A Chronological Review of Techniques.
International Journal of Special Education, 41(25s), 254-268

ABSTRACT:

Lightning remains a persistent cause of fatalities, structural damage, and interruption of power, data, and communication services worldwide. Techniques for quantifying lightning risk have changed rapidly as observational networks, protection standards, and computational methods advanced, yet no chronological synthesis maps how assessment practice itself has evolved. Hence, this review addresses that gap. A single-step systematic search of the Scopus database was conducted using the terms lightning, lightning risk assessment, and climate change, restricted to English-language journal articles at the final publication stage within the Engineering and Energy subject areas between 2016 and 2026. The search returned 93 primary articles. Optimal contiguous partitioning of annual output identified three phases. Phase I, Standards Consolidation (2016–2019, $n = 26$, 6.5 articles annually), was governed by International Electrotechnical Commission-IEC6254-268, with ground flash density supplying the exposure term. Phase II, Exposure Metric Refinement (2020–2023, $n = 32$, 8.0 annually), introduced Bayesian networks, spatio-temporal statistics, and assessment of previously unconsidered receptors. Phase III, Data-Driven and Asset-Specific Assessment (2024–2026, $n = 35$, 11.7 annually), features gradient boosting, explainable modeling, and asset-specific economic quantification. Only the 2023/2024 transition reached statistical significance ($p = 0.035$).

COPYRIGHT STATEMENT:

Copyright: © 2026 Authors.
Open access publication under the
terms and conditions
of the Creative Commons Attribution
(CC BY)
license (<http://creativecommons.org/licenses/by/4.0/>).

Documented advances include ground strike point density exceeding flash density by up to 32 strike points per square kilometer annually, nowcasting detection probabilities approaching 98%, and lightning accounting for 24.84% of Brazilian transmission line failures. The chronology demonstrates progressive displacement of deterministic standard application by probabilistic, asset-specific inference.

Keywords: Lightning protection system, Ground strike point density, Lightning location system, Lightning risk assessment, Climate change.

1. Introduction

Lightning risk assessment has evolved from simple regional exposure estimates into a multidisciplinary effort to quantify where lightning occurs, how it attaches, what it damages, and which protection measures reduce losses most effectively. Early practice treated lightning risk mainly as a function of ground flash density, first inferred from thunderstorm-day or keraunic-level data and later derived directly from lightning location systems as observational networks improved (Poelman et al., 2021). This shift from climatological proxy to instrumental measurement mattered since lightning is a recurrent source of fatalities, damage to structures and services, transformer failures, and damaging surges entering buildings through power, data, and communication lines (Abulaban & Siow, 2021a; Houard et al., 2022; Tanwer et al., 2024). Early protection practice, therefore, centered on interception and shielding, especially the Franklin rod, while later alternatives, such as Early Streamer Emission systems, appeared in some countries after radioactive air terminals were banned (Deb & Verma, 2025; Tanwer et al., 2024; Ullah et al., 2022). Even in that early phase, however, the central engineering problem was broader than counting strikes, since risk depended on injuries, physical damage, internal system failure, and economic loss rather than attachment alone (Rousseau, 2021). The major turning point came with IEC 6254-268, which formalized lightning risk as the combination of event frequency, damage probability, and loss magnitude, and compared the resulting risk against tolerable thresholds to determine whether more protection was justified (Rousseau, 2021).

That framework distinguished four sources of damage and linked them to graded protection levels from IV to I, making lightning protection a cost-performance optimization issue rather than a purely geometric design exercise (Rousseau, 2021). It also became the benchmark in many countries. Despite this, national deviations and application-specific adaptations were common, as the same standard had to serve small buildings, oil tanks, renewable energy assets, and power systems with varying operating conditions (Abulaban & Siow, 2021a). At the same time, practitioners recognized that full standard-based assessment is labor-intensive and not consistently aligned with specialized assets such as high-voltage substations. Consequently, failures still occur despite installed protection, and ambiguous factors often required adjustment (Lim et al., 2022; Rousseau, 2021).

The next chronological advance questioned whether the standard exposure metric itself was too coarse. Ground flash density remained the dominant regional input. Nevertheless, high-speed observations and stroke analyses have demonstrated that many flashes terminate at more than one ground-strike point. Hence, flash counts alone understate the number of actual threat locations (Poelman et al., 2021). This insight led to the argument that **ground strike point density** should replace, or at least complement, flash density in lightning protection studies (Poelman et al., 2021). Modern lightning location systems made this transition increasingly feasible by locating strokes with sufficient accuracy for grouping algorithms to reconstruct distinct strike points from stroke-level observations (Poelman et al., 2021). Furthermore,

validation across datasets from Austria, Brazil, France, Spain, South Africa, and the United States revealed that these algorithms can accurately identify stroke type with success rates up to about 90%. Nonetheless, performance depends strongly on location accuracy and stroke peak current (Poelman et al., 2021). The practical consequence is substantial: in South Africa, ground flash density underestimated lightning risk across the entire landscape, with local differences reaching 32 ground-strike points per square kilometer per year (S. Gcaba & Hunt, 2024). Where stroke-level processing is unavailable, a constant scaling factor can serve as a pragmatic correction, though recent work suggests that multiplicity is only part of the problem (S. Gcaba & Hunt, 2024) (Gcaba & Hunt, 2024). Statistical analyses from China illustrate that Poisson-style models based on ground flash density oversimplify lightning dynamics, as observed flashes exhibit spatial clustering, temporal persistence, and interannual dependence, thereby underestimating localized hotspots during active periods (Yi et al., 2025). This finding has pushed the field toward localized spatiotemporal models and even toward three-dimensional descriptors such as *volume lightning strike density*. The latter has been proposed as an alternative or complementary measure to characterize lightning presence for critical sites where surface counts alone may not capture interception geometry (Ioannidis & Tsovilis, 2023).

More recent techniques extend the chronology from static hazard mapping to predictive, data-driven, and physics-based assessments tailored to specific decisions and infrastructure. For human safety, spatiotemporal models now combine lightning-mapping observations, interpolation, and IEC-derived probabilistic calculations to issue warnings. This has resulted in fewer failures than a standard proximity-based method, yet with longer warning times and higher false-alarm ratios (Murphy et al., 2021). Building on this, parallel spatial-analysis studies integrate lightning distribution with land use, rainfall, humidity, and population density to identify high-risk zones and support mitigation planning, while emphasizing

the need for empirical validation and temporal updating (Andru et al., 2023). Forecasting for aviation has similarly shifted toward threshold-based, neural-network, and belief-function tools, with no single best method since users must trade off false alarms, missed detections, and runtime (Bouchard et al., 2022). Renewable energy systems now play a major role in lightning risk research since taller wind turbines and large photovoltaic plants are both exposed and economically sensitive (Sumetha-Aksorn & Dykes, 2024; Q. Zhou et al., 2023b). Furthermore, offshore wind-farm studies use semi-supervised learning when labeled data are scarce and report higher risk in areas with many turbines, high lightning density, and strong lightning intensity, while also incorporating lightning-protection capability via receptor number (Q. Zhou et al., 2023b). Additionally, data-driven turbine models extend IEC-style equations to account for residual real-world risk, including degraded receptors, maintenance status, repair costs, and downtime. These models demonstrate that site-specific economics can dominate total lightning risk, especially in offshore environments (Sumetha-Aksorn & Dykes, 2024). At the physics end of the timeline, improved stochastic turbine models now account for current amplitude, polarity, turbine height, and blade rotation. They appear to agree better with observations than the IEC-recommended method since they are tied to the attachment process itself (Bian et al., 2023). Small-scale experiments on upward leader inception around air terminals support the same physical turn by revealing that local electric fields can predict strike attachment on installed terminals (Ullah et al., 2022). In line with this, debate persists over non-conventional interception, with one photovoltaic case study reporting lower installation cost and effective five-year operation for an ESE system. Nonetheless, broader reviews conclude that claims of superior Early Streamer Emission (ESE) lightning rod performance remain unsubstantiated and unendorsed by major standards organizations (Gomes, 2025; Kongnok et al., 2021). New rod geometries such as multi-spoke designs and the first field demonstration of laser-guided lightning suggest that the latest stage

of lightning risk techniques may extend beyond passive interception toward more actively controlled discharge paths (Deb & Verma, 2025; Houard et al., 2022).

2. Materials and Methods

2.1 Data Collection

Lightning causes fatalities, damages structures, and interrupts power, data, and communication services. The methods used to quantify that risk have changed as observation, standardization, and computation have improved. Tracing those changes requires a corpus built under stated rules, since a chronological argument rests on the sample from which its timeline is drawn. Accordingly, data were collected in a single step from Scopus, which indexes the engineering, atmospheric science, and energy literature covered by this review, and applies consistent metadata fields across all three domains. Following this, a Boolean query was executed to combine lightning-related terms with risk, protection, and assessment descriptors across the title, abstract, and keyword fields, yielding 93 records for subsequent screening. The eligibility criteria were established before conducting the search rather than refined after inspecting the results. These criteria included English-language

publications between 2016 and 2026. Titles and abstracts were screened against the defined thematic scope, resulting in 93 eligible publications. In particular, establishing the protocol before conducting the review limits the discretion that could introduce selection bias into a narrative review, allowing any reader with database access to repeat the search process. Three properties of the synthesis depend on this methodological discipline. A corpus that cannot be recovered cannot be independently audited, which is essential for ensuring reliability. The inclusion criteria were chosen to track genuine methodological change, not ease of retrieval, so the papers examined reflect real shifts in method rather than whichever studies were simplest to locate. Temporal interpretation carries the heaviest burden. Readers can distinguish real shifts in emphasis, from keraunic proxies to instrumental flash density, from flash counts to ground strike points, from deterministic standards to data-driven models, and from artifacts arising from indexing coverage only when the retrieval window and inclusion criteria remain consistent throughout the review period. The protocol is reported in full to allow readers to assess which observed trends reflect developments in the field and which may be attributable to the search strategy.

Table 1: The specification for primary data searching.

Keyword	Lightning, lightning risk assessment, climate change
Inclusion	Article, Journal, English, engineering, and energy
Exclusion	Besides the engineering and energy area, review articles, and other languages
Final Search String (Scopus)	TITLE-ABS-KEY (lightning risk assessment) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (SRCTYPE , ";")) AND (LIMIT-TO (PUBSTAGE , "final")) AND (LIMIT-TO (SUBJAREA , "ENGI") OR LIMIT-TO (SUBJAREA , "ENER")) AND (LIMIT-TO (EXACTKEYWORD , "Lightning") OR LIMIT-TO (EXACTKEYWORD , "Lightning Risk Assessment") OR LIMIT-TO (EXACTKEYWORD , "Climate Change")) AND PUBYEAR > 2015 AND PUBYEAR < 2027
Number of Primary Articles	93

The search was performed in Scopus in a single step on 8 August 2026 using the string reported in Table 1. The query anchors on TITLE-ABS-KEY (lightning risk assessment). Hence, every retrieved record focuses on risk assessment rather than on lightning physics or detection alone. Five restrictions then narrowed the set. Limiting the document type to article, the source type to journal, and the publication stage to final confines the corpus to peer-reviewed primary research whose pagination and content will not change, allowing any reader to repeat the search and retrieve the same records. Meanwhile, restricting language to English reflects the working language of the indexed protection-engineering literature. Additionally, restricting the subject areas to Engineering and Energy aligns the corpus with the review's focus on protection design, standards compliance, and infrastructure exposure, rather than atmospheric physics. Requiring at least one indexed keyword from Lightning, Lightning Risk Assessment, or Climate Change enforces topical centrality, since an author who mentions lightning risk in passing will not assign it as a keyword. The publication window was set from 2016 to 2026. Applying all criteria in a single retrieval step, rather than refining the query after inspecting the results, reduces the potential for iterative judgment that may introduce selection bias into a narrative review. Consequently, the search returned 93 primary articles.

Each restriction trades recall for precision, and the corpus size makes that trade explicit. The keyword clause is the most aggressive filter in the string and does most of the reduction. Specifically, it discards papers indexed under related yet distinct terms, such as lightning protection, ground flash density, or IEC 62305, thereby almost certainly excluding relevant work. The trade-off is justified since a chronological argument depends on reading every article rather than counting them. Ninety-three articles across 11 years support a technique-by-technique reading of the full corpus. In contrast, a recall-optimized search returning several hundred would force sampling, reintroducing the discretion the protocol was designed to remove.

Moreover, precision also protects the temporal claim. When inclusion rules hold constant across the window, an observed shift in the method reflects the field rather than a drift in indexing coverage. Three limitations follow from these choices and bound the conclusions. Confining the search to Scopus omits conference proceedings, and the International Conference Lightning Protection (ICLP) and International Symposium on Lightning Protection (SIPDA) series carry substantial protection-engineering work. Meanwhile, restricting the subject area to Engineering and Energy omits atmospheric and environmental science venues where lightning-climate research also appears. Beginning in 2016, the analysis is restricted to the most recent decade. Therefore, this review traces recent methodological change rather than the field's full history.

2.2 Data Clustering

A chronological review should go beyond simply listing publications in date order. Ordering alone yields a sequence rather than an argument, leaving the reader to infer where one methodological era closes and the next opens. Grouping converts an ordered series into a small number of interpretable units, each of which can be characterized in its own terms, compared against its neighbors, and tested for internal coherence. That logic was applied to the 93 articles retrieved from Scopus under the search protocol reported in Section 2. Notably, two considerations govern the partition. Phases must correspond to identifiable shifts in technique, since this review examines how researchers quantify lightning risk rather than how much they publish about it. The partition rule must also be fixed in advance and applied without adjustment to ensure that any reader can reproduce the boundaries from the same annual counts. Accordingly, the contiguous three-way partition that minimizes within-cluster variance in annual output was selected, and the resulting boundaries were examined against documented changes in method. Reporting publication volume alongside the thematic characterization serves a specific purpose. It assesses whether a claimed methodological turn attracted measurable

research effort or remained confined to a narrow literature. When volume and technique shift together, the boundary carries weight. Conversely, where they diverge, the divergence itself becomes informative and is reported

accordingly rather than being suppressed. The following sections present the three phases, their annual outputs, and the statistical support for each boundary, as illustrated in Figure 1.

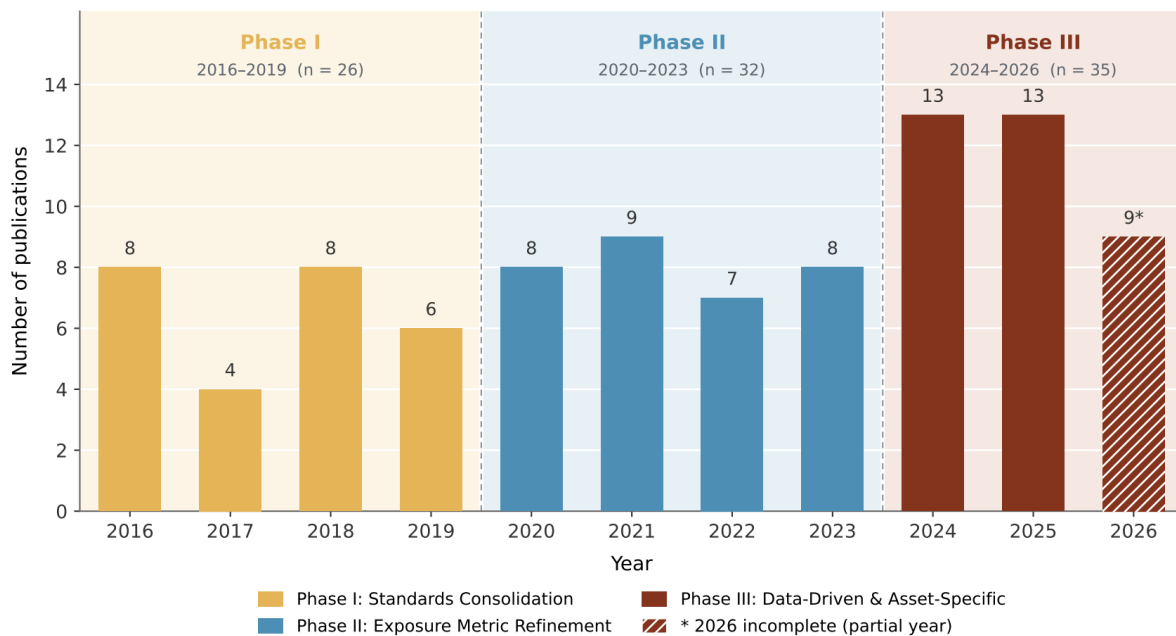


Figure 1. Annual publication output by chronological phase, 2016–2026 (n = 93; 2026 partial)

2.2.1 Phase I (2016–2019): Standards Consolidation

Work in this period operates within the framework established by IEC 6254-268. Authors treat lightning risk as the product of event frequency, damage probability, and loss magnitude, and compare the computed risk against tolerable thresholds to determine whether additional protection is warranted. Ground flash density supplies the exposure term throughout. Research effort concentrates on applying the standard to asset classes it was not written for, on national deviations, and on the unresolved dispute over Early Streamer Emission terminals. Specifically, the output rate averages 6.5 articles per year, the lowest of the three phases, which is consistent with a field applying a settled framework rather than contesting it.

2.2.2 Phase II (2020–2023): Exposure Metric Refinement

Attention shifts from applying the framework to auditing its inputs. Authors demonstrate that a

single flash may terminate at several ground strike points. Therefore, flash counts understate the number of threat locations, and they propose ground strike point density as a replacement or complement. Additionally, improved lightning location systems make stroke grouping feasible, and validation studies across multiple national datasets test how well those algorithms recover strike points. Parallel statistical work portrays that Poisson models built on flash density miss spatial clustering and interannual persistence, thereby pushing the field toward localized spatio-temporal descriptors. Output rises to 8.0 articles per year, though the increase over Phase I is not statistically significant.

2.2.3 Phase III (2024–2026): Data-Driven and Asset-Specific Assessment

Phase III is the most productive phase, at 11.67 articles per year, and the only one separated from its predecessors by a significant volume break. Research shifts from static hazard mapping toward prediction and toward risk models built

for named infrastructure. As such, machine learning is applied to nowcasting, warning systems, and semi-supervised classification for offshore wind farms, where labeled data are scarce. Concurrently, turbine and photovoltaic studies extend IEC-style equations to account for residual real-world risks by incorporating receptor degradation, maintenance state, repair costs, and downtime, and find that site economics can dominate the total. At the physical end, stochastic attachment models accounting for blade rotation and current polarity begin to outperform the standard method, while the first field demonstration of laser-guided lightning signals interest in actively controlled discharge paths.

3. Results and Discussion

3.1 Standards Consolidation (2016 – 2019)

Findings reported during 2016 and 2017 concentrate on quantifying risk within established standard frameworks. (D. Wu & Chen, 2016) obtained rim seal fire probabilities of 1.10×10^{-2} and 4.99×10^{-2} across two accident categories, and concluded that rim seal fire risk remains unacceptable unless inert gas protection is introduced. (Necci et al., 2016) embedded lightning-triggered accidents within quantitative risk assessment and demonstrated measurable risk reduction from alternative protection strategies, which advanced the field toward risk-based design of protection systems. Furthermore, (Lo Piparo et al., 2016) established the probabilistic basis for selecting coordinated surge-protective devices under source of damage S1. (Grujić & Stojković, 2016) adapted IEC 6254-268 to high-voltage substations, which lie outside its declared scope, and produced risk maps as a function of impulse current for 220 kV and 110 kV installations. (Ghaffarzadeh, 2016) reported that a wavelet network estimated failure risk in a 230 kV network with better accuracy than existing methods at a mean computation time of 54s. (Pantoja et al., 2017) identified that an unconnected metallic fence posed a lower human safety risk than a connected one, a result that contradicts common grounding practice.

Results published during 2018 and 2019 indicate growing attention to standard inadequacy and to economic quantification. (Becerra et al., 2018) determined that IEC 6254-268 underestimates dangerous lightning frequency at offshore wind plants. The study estimated that fewer than 19% of thunderstorms generate fields capable of self-initiating upward lightning, with upward flashes triggered by nearby positive cloud-to-ground events causing the most damaging incidents. Liu et al. also demonstrated that protective measures reduced the risk of human life loss from 21.299×10^{-5} to 0.439×10^{-5} and the economic risk from 2696.754×10^{-5} to 98.062×10^{-5} , yielding annual savings of \$876,365. (Sarajcev et al., 2018) introduced a backflashover risk indicator linking incident current probability to backflashover current distribution, then related the resulting figure to investment cost. Additionally, (Mahmood et al., 2019) established that surge arrester spacing below 200 m improves medium-voltage line performance, and that combining arresters with shield wire permits wider spacing. Rodrigues et al. further reported shielding failure widths of 12, 8, 4, and 0 m across four current levels and illustrated that horizontally shifting arrester cables by 5 to 8 m halved the failure width at 3.9 kA. (Gu et al., 2019) obtained an effective warning ratio of 73% from a backpropagation neural network integrating detection, electric field, and radar data.

Overall, findings from 2020 indicate a movement toward probabilistic learning methods and consequence modeling. (Sarajcev et al., 2020) applied Bayesian learning and Gaussian process regression to lightning location system records, generating probabilistic damage risk alongside monetized loss estimates suitable for insurers. (Misuri et al., 2020) depicted that including domino escalation raises calculated risk by up to two orders of magnitude relative to conventional scenarios. Moreover, (Rodríguez-Pérez et al., 2020) compared five prediction methods and revealed that a generalized additive model with a spatial trend was most appropriate, reporting that lightning-caused fire probability depends nonlinearly on the proportion of coniferous woodland rather than on topography, climate, or

lightning characteristics. Sabiha et al. verified that a spark gap installed in parallel with a surge arrester relieves thermal stress and reduces the risk of failure. (Yousefpour et al., 2020) established that insulating ground electrode edges prevent discharge current from bypassing composite specimens, indicating that uninsulated configurations understate damage. (Xie et al., 2020) confirmed that finite difference time domain calculation of induced voltage yields more accurate trip rates than formula-based estimation.

3.2 Exposure Metric Refinement (2020 - 2023)

Results published in 2021 indicate a shift toward data-driven characterization of exposure. (Tian et al., 2020) weighted an improved analytic hierarchy process using association-rule lift and reported 76% agreement between estimated and observed trip-out risk across 28 lines rated at 220 kV. (He et al., 2021) examined 436 airports in the United States, establishing that southern airports remain most exposed irrespective of flash intensity, while k-means clustering yielded five exposure profiles and isolated airports whose exposure current standards understate. Furthermore, (Bao et al., 2021) linked thunderstorm duration to trip-out probability using a fragility function, finding that the high-risk group's average risk was about 10 times that of the low-risk group in Southwest China. (Y. Zhang et al., 2021) combined k-means resampling, a neural network, and Jenks natural breaks zoning to reach 81% accuracy. (Izadi et al., 2021) derived striking points from measured induced voltages, yielding flash density maps for subsequent assessment. Additionally, (Cheng & Luo, 2021) demonstrated that a Bayesian network can capture direct causal relationships among Natech risk factors and support predictive and diagnostic analyses. (Androvitsaneas et al., 2021) compiled 10 years of Hellenic wind farm flash and ground resistance data, whereas (Abulaban & Siow, 2021b) documented national deviation from IEC 62305 and Malaysian nationalization. (Mitolo et al., 2021) identified the critical trunk radius below which a struck tree may explode and ignite adjacent vegetation.

Work in 2022 focused on extending the assessment of novel receptors and using machine learning for occurrence prediction. (Chun Lim et al., 2022) determined that fire load function, environmental factor, and lightning protection level are the ambiguous factors requiring adjustment when IEC 6254-268 is applied to high-voltage substations, which it does not cover. (La Fata et al., 2022) reported random forest nowcasting over Italy performs best when all inputs share the finest available grid, with upper-air meteorological variables outweighing topographic descriptors such as elevation and latitude. Liu et al. improved overhead line failure evaluation accuracy by correcting the mass function in Dempster-Shafer theory using entropy-based weighting and gray relational analysis. Similarly, (B. Chen & Jin, 2022) separated ignition sources in California and reported lightning ignitions concentrated in remote Sierra Nevada and North Interior terrain, governed by snow water equivalent, strike density, and fuel load. Shu et al. observed a peak lightning fire frequency between 600 and 700 m in the northern Daxing'an Mountains, with rising frequency from 1999 to 2019 despite no corresponding increase in affected area. The study also identified a positive correlation with temperature and evaporation, and a negative correlation with precipitation and soil moisture. (L. Zhou et al., 2022) measured grass carp conductivity and current reaction thresholds, confirming that protective measures reduce adverse response near distribution earthing devices.

Findings from 2023 reveal consolidation around Bayesian and semi-supervised frameworks alongside renewed field measurement. (Q. Zhou et al., 2023a) applied semi-supervised k-means with a Laplacian support vector machine tuned by particle swarm optimization, outperforming standard support vector machines and neural networks, and reported elevated risk where turbine count, flash density, and strength are jointly high, with ocean areas tending lower. (Gao et al., 2023) quantified economic and social trust loss for overhead contact lines through a three-layer Bayesian network, while (J. Wang et al.,

2023) embedded lightning identification, tracking, and trajectory prediction into a Bayesian reliability model accounting for imperfect maintenance and common cause failure. Additionally, (Tasman et al., 2023) measured charge transfer during continuing current in Johannesburg, obtaining 0.3 to 145.5 C (mean 18.3 C) across 34 negative strokes and 3.7 to 66.6 C across five positive strokes, comparable to Brazilian observations yet exceeding Austrian and United States averages. (Deng et al., 2023) reported a correlation coefficient of 0.473 between flash density and environmental sensitivity in Yunnan. (Xu et al., 2023) estimated distribution network risk under storm pre-warning and proposed topology reconstruction as preventive control. Pompili et al. concluded that adding partial-discharge and acceleration-voltage measurements improves the evaluation of alternative transformer dielectric liquids.

3.3 Data Driven and Asset Specific Assessment (2024 – 2026)

Results from 2024 focus on replacing coarse exposure metrics and machine-learning detection. (S. T. Gcaba & Hunt, 2024) applied a ground strike point algorithm to nine years of Southern African Lightning Detection Network records and established that ground flash density underestimates risk across the entire South African landscape, reaching 32 ground strike points per square kilometer annually between Mpumalanga and KwaZulu-Natal. On the other hand, (Stucke et al., 2024) demonstrated at the Gaisberg Tower that conventional location systems miss roughly half of upward events, that wind-field environments account for nearly all such events in cold seasons, and that a random forest trained on meteorological variables alone generalizes to turbines elsewhere. (Yin et al., 2024) obtained a detection probability of 89%, a false-alarm ratio of 30%, and a Heidke skill score of 0.77 from nowcasting based on precipitable water vapor. In comparison, (Ain et al., 2024) reported a 98% detection probability, a critical success index of 75.2%, and a reliability improvement of nearly 78% under dynamic microgrid control. (Ning et al., 2024) determined lightning most threatening to transformers

among turbine sub-assemblies, second overall after wind. (Tushemereirwe et al., 2024) recorded 10 children killed and four injured in Uganda amid an absent official response. Additional contributions covered high-risk 750 kV towers (H. Zhang et al., 2024), generative adversarial modeling of distribution risk (H. Wang et al., 2024), flange failure where spark gap cable voltage exceeds dielectric strength (Dimitriou et al., 2024), cloud-based outage prediction (Gruzdov et al., 2024), Hellenic vulnerability mapping under Representative Concentration Pathway 8.5 (RCP 8.5) (Gkika et al., 2024), spaceborne detector verification (T. Zhang et al., 2024), and nanofluid gains reaching 60% for titanium dioxide (Q. Chen et al., 2024).

Furthermore, findings from 2025 emphasize gradient boosting, explainability, and quantified protection benefit. (Zou et al., 2025) achieved precision and recall of 98.9% from a Bayesian-optimized extreme gradient boosting model for tropical cyclone lightning at offshore farms, outperforming long short-term memory and support vector machine baselines. (Q. Zhang et al., 2025) reached 85.81% out-of-sample accuracy predicting lightning-ignited wildfires in Texas, exceeding the fire weather index and random forest, with ignition governed by flash frequency, temperature, and fuel moisture. (Zou et al., 2025) quantified that adequate protection lowers strike probability by 22.5%, and thicker tank walls reduce failure probability up to 4.2%. (Tang et al., 2025) reported average gains of 21% and 8.3% in Area Under the Receiver Operating Characteristic (AUROC) over baselines. (Lobato et al., 2025) revealed backflashover rates highly sensitive to footing impedance, a leader progression model yielding roughly 10% lower estimates than the Eriksson model at 20 ohms. (Harding et al., 2025) established that lightning caused only 5% of California fires, yet accounted for over one quarter of burned acreage. (Rogers & Ollson, 2025) demonstrated that blade debris beyond 1.1 times the tip height, carried at low kinetic energy, is unlikely to injure. (Kim et al., 2025) ranked lightning among the top five climate hazards for Korean nuclear plants via Delphi elicitation, (Lee et al., 2025) linked Alaskan

warming to concurrent lightning increase and fire potential, and (Neyshabouri & Niasati, 2025) examined grounding and shunt configuration for floating roof tanks.

Work during 2026 combines satellite observations, explainable modeling, and human safety. [75] reported that lightning was responsible for 24.84% of Brazilian transmission failures, with a mean flash density of 5.02 per square kilometer annually and a maximum of 21.85, and monthly occurrence correlated with failures at 0.77. (Kwon & Park, 2026) identified 34 clusters occupying about 5% of the time yet containing about 70% of strokes in Korea, oriented northwest to southeast. (Beetz, 2026) simulated step and touch voltages, concluding outdoor exposure very likely produces fatal heart currents, whereas indoor risk remains low. Moreover, (Deng et al., 2026) diagnosed tower risk causes through Shapley additive explanations with a surrogate network, (Yao et al., 2026) depicted higher current and smaller rotation angles raise single-blade attachment, (Charalambous et al., 2026) attributed Hellenic gas pipeline damage to coating defects, (Thakur, 2026) applied IEC 6254-268 to explosive structures accounting for occupancy duration, and (C. Wu & Xue, 2026) proposed integrated wildfire defense.

4. Conclusion

This review traced the development of techniques for assessing lightning risk over the past decade. A single-step systematic search of the Scopus database returned 93 primary journal articles published between 2016 and 2026 within the engineering and energy subject areas. The objective was not merely to synthesize the literature thematically. Instead, it aims to establish when particular methods entered practice, which assumptions were revised, and how the field's analytical basis shifted across successive periods.

In particular, three phases emerged from the analysis. During Standards Consolidation (2016–2019), assessment operated inside the framework defined by IEC 6254-268, combining event frequency, damage probability, and loss magnitude, with ground flash density supplying

the exposure term and effort directed toward asset classes the standard did not explicitly cover. Exposure Metric Refinement (2020–2023) redirected attention from applying that framework to auditing its inputs. Evidence that a single flash may terminate at multiple ground-strike points undermined confidence in flash counts, while statistical work demonstrated that Poisson formulations based on flash density fail to capture spatial clustering and interannual persistence. Furthermore, Data-Driven and Asset-Specific Assessment (2024–2026) is distinguished by predictive modeling, explainable machine learning, and risk formulations constructed for named infrastructure, in which economic consequence, maintenance state, and protection capability are entered directly into the calculation. Mean annual output increased from 6.5 to 8.0 and subsequently to 11.67 articles across the three periods.

The dominant pattern across the timeline is the shift from deterministic, geometry-based design to probabilistic and data-driven inference. Gradient boosting, Bayesian networks, semi-supervised classification, and Shapley-based attribution progressively supplemented tabulated risk factors. In contrast, satellite and ground detection networks supplied the observational density that such methods require. This trajectory indicates a maturing domain in which standards function as a reference point rather than as the analytical endpoint.

Organizing the literature chronologically adds an interpretive dimension that thematic synthesis does not. Grouping by period exposes the sequence in which assumptions were challenged and clarifies that metric refinement preceded, and made possible, the later data-driven turn. Practically, the findings indicate that exposure inputs derived solely from flash density may understate hazard, that asset-specific economic parameters materially alter computed risk, and that explainable models offer a route toward protection decisions that practitioners can audit and defend.

Notably, several limitations qualify these conclusions. Reliance on a single database omits

conference proceedings that carry substantial protection-engineering work. Restriction to engineering and energy subject areas excludes atmospheric and environmental venues, and the 11-year window confines the analysis to recent methodological change rather than the full history of the discipline. Keyword restriction further favored precision over recall. Therefore, future work should extend across databases and disciplines, validate machine learning models against operational failure records rather than curated datasets, and examine how revised exposure metrics perform under field conditions in tropical and mountainous terrain.

Chronological review remains a valuable instrument for capturing how a scientific field actually changes. By linking methods to periods, time-based analysis separates genuine progress

from repetition and provides a structured foundation for guiding future innovation in lightning protection.

5. Acknowledgements

The authors acknowledge financial support from Universiti Tun Hussein Onn Malaysia (UTHM) under Grant Tier 1 (J134) and Universiti Putra Malaysia (UPM) under the IPB Grant GP-GPB/2022/9708800

6. Author Declaration

We confirm that this manuscript is original, has not published previously and is under consideration for publication elsewhere, in whole or part.

The authors declare no conflicts of interest related to this research

References

- Abulaban, H., & Siow, C. (2021a). Recent Progress on Lightning Risk Assessment and its Applications in Malaysia. *International Review of Electrical Engineering-Iree*, 16, 41. <https://doi.org/10.15866/iree.v16i1.18426>
- Abulaban, H., & Siow, C. L. (2021b). Recent progress on lightning risk assessment and its applications in Malaysia. *International Review of Electrical Engineering*, 16(1), 41–49. <https://doi.org/10.15866/iree.v16i1.18426>
- Ain, N. U., Mahmood, F., Tong, C., Vagasky, C., & Rizk, M. E. M. (2024). Lightning nowcasting using fuzzy logic — A risk assessment framework for resilience of microgrids. *Electric Power Systems Research*, 230. <https://doi.org/10.1016/j.epsr.2024.110253>
- Androvitsaneas, V. P., Damianaki, K. D., Nicolopoulou, E. P., & Gonos, I. F. (2021). Statistical analysis of lightning flashes over wind parks in Greece. *Energies*, 14(19). <https://doi.org/10.3390/en14196076>
- Andru, A., Amarsin, A., & Yasir, A. M. (2023). Model of Lightning Strike Risk to Humans Based on Spatial Analysis and Environmental Factors. *Journal of Computation Physics and Earth Science (JoCPES)*. <https://doi.org/10.63581/jocpes.v3i1.05>
- Bao, J., Wang, X., Zheng, Y., Zhang, F., Huang, X., Sun, P., & Li, Z. (2021). Resilience-Oriented Transmission Line Fragility Modeling and Real-Time Risk Assessment of Thunderstorms. *IEEE Transactions on Power Delivery*, 36(4), 2363–2373. <https://doi.org/10.1109/TPWRD.2021.3066157>
- Becerra, M., Long, M., Schulz, W., & Thottappillil, R. (2018). On the estimation of the lightning incidence to offshore wind farms. *Electric Power Systems Research*, 157, 211–226. <https://doi.org/10.1016/j.epsr.2017.12.008>
- Beetz, D. (2026). Risk analysis of lightning-caused body currents by modeling a human being using lumped elements. *Electric Power Systems Research*, 260. <https://doi.org/10.1016/j.epsr.2026.113327>
- Bian, X., Wu, Y., Zhou, Q., Jiang, R., Zhang, Y., Chen, L., Qi, Q., & Lyu, W. (2023). Simulation of Cloud-to-Ground Lightning Strikes to Wind Turbines Considering Polarity Effect Based on an Improved Stochastic Lightning Model. *Atmosphere*. <https://doi.org/10.3390/atmos14010108>
- Bouchard, A., Buguet, M., Chan-Hon-Tong, A., Dezert, J., & Lalande, P. (2022). Comparison of different forecasting tools for short-range lightning strike risk assessment. *Natural Hazards*, 115, 1011–1047. <https://doi.org/10.1007/s1254-268-05546-x>
- Charalambous, C. A., Dimitriou, A., Kokkinos, N., Kioupis, N., & Manolis, T. (2026). Lightning strikes and buried gas pipelines: Mechanisms, risk assessment, mitigation, and case insights from the hellenic gas transmission system. *Electric Power Systems Research*, 255. <https://doi.org/10.1016/j.epsr.2026.112809>

- Chen, B., & Jin, Y. (2022). Spatial patterns and drivers for wildfire ignitions in California. *Environmental Research Letters*, 17(5). <https://doi.org/10.1088/254-268/ac60da>
- Chen, Q., Beroual, A., Sima, W., & Sun, P. (2024). AC and Lightning Impulse Breakdown Voltage Comparative Study of Mineral Oil-Based Fe₃O₄, Al₂O₃, and TiO₂Nanofluids. *IEEE Transactions on Dielectrics and Electrical Insulation*, 31(1), 278–287. <https://doi.org/10.1109/TDEI.2023.3309770>
- Cheng, Y., & Luo, Y. (2021). Analysis of Natech risk induced by lightning strikes in floating roof tanks based on the Bayesian network model. *Process Safety Progress*, 40(1). <https://doi.org/10.1002/prs.12164>
- Chun Lim, S., Chang Shen, O., & Eng Eng, N. (2022). An Integrated Lightning Risk Assessment of Outdoor Air-Insulated HV Substations. *Energies*, 15(20). <https://doi.org/10.3390/en15207702>
- Deb, R., & Verma, A. (2025). Comparative Analysis of Multi-spoke Lightning Rod to conventional ESE and Franklin Rod. *2025 IEEE International Conference on Power Electronics, Smart Grid, and Renewable Energy (PESGRE)*, 1–4. <https://doi.org/10.1109/pesgre65581.2025.11521116>
- Deng, Y., He, X., Wang, Y., Lan, L., & Du, Z. (2026). SHAP-Based Interpretable Neural Network Framework for Lightning Risk Analysis and Diagnosis in Power Transmission Lines. *IEEE Transactions on Power Delivery*, 41(4), 1783–1790. <https://doi.org/10.1109/TPWRD.2026.3678291>
- Deng, Y., Li, M., Wang, Y., He, X., Wen, X., Lan, L., Ma, Y., & Pan, H. (2023). Relationship between Lightning Activity and Terrain in High-Altitude Mountainous Areas. *IEEE Transactions on Power Delivery*, 38(5), 3561–3570. <https://doi.org/10.1109/TPWRD.2023.3283606>
- Dimitriou, A., Melios, C., Kokkinos, N., & Charalambous, C. A. (2024). Advancing lightning risk assessment of pipeline insulating flanges with isolating spark-gap. *Electric Power Systems Research*, 230. <https://doi.org/10.1016/j.epsr.2024.110214>
- Gao, S., Wang, J., Yu, L., Zhang, D., Zhan, R., Kou, L., & Chen, K. (2023). A Multilayer Bayesian Network Approach-Based Predictive Probabilistic Risk Assessment for Overhead Contact Lines Under External Weather Conditions. *IEEE Transactions on Transportation Electrification*, 9(1), 236–253. <https://doi.org/10.1109/TTE.2022.3198554>
- Gcaba, S., & Hunt, H. (2024). Underestimating lightning risk due to multiple Ground Strike Point flashes. *Electric Power Systems Research*. <https://doi.org/10.1016/j.epsr.2024.110498>
- Gcaba, S. T., & Hunt, H. G. P. (2024). Underestimating lightning risk due to multiple Ground Strike Point flashes. *Electric Power Systems Research*, 233. <https://doi.org/10.1016/j.epsr.2024.110498>
- Ghaffarzadeh, N. (2016). A new wavelet network based method to estimate the lightning-related risk of failure of power system apparatus. *International Journal of Electrical Power and Energy Systems*, 78, 375–384. <https://doi.org/10.1016/j.ijepes.2015.11.109>
- Gkika, A. V., Lympieri, O.-A. I., Varouchakis, E. A., Pavlides, A., Zacharis, E. A., & Lekkas, E. L. (2024). A risk assessment methodology for supporting decision making on the climate proofing of electricity distribution networks. *Energy Reports*, 12, 6155–6185. <https://doi.org/10.1016/j.egyr.2024.11.070>
- Gomes, C. (2025). Early Streamer Emission Lightning Protection Systems: Global Views Revisited. *2025 13th Asia-Pacific International Conference on Lightning (APL)*, 324–329. <https://doi.org/10.1109/apl65034.2025.11108737>
- Grujić, A., & Stojković, Z. (2016). Fuzzy logic-based concept for high-voltage substation risk management against lightning. *IEEE Transactions on Electrical and Electronic Engineering*, 11, S28–S36. <https://doi.org/10.1002/tee.22233>
- Gruzdev, A. G., Voloshin, A. A., & Voloshin, E. A. (2024). Development of a Cloud Service for Forecasting Power Outages of Consumers With Damage Assessment Based on Thunderstorms Data. *IEEE Transactions on Industry Applications*, 60(5), 7491–7499. <https://doi.org/10.1109/TIA.2024.3408722>
- Gu, S., Wang, J., Wu, M., Guo, J., Zhao, C., & Li, J. (2019). Study on lightning risk assessment and early warning for UHV DC transmission channel. *High Voltage*, 4(2), 144–150. <https://doi.org/10.1049/hve.2018.5081>
- Harding, A. B., Tarr, G. A. M., & Ramirez, M. R. (2025). Only Who Can Prevent Forest Fires? Causes of a Subset of Wildfires in California, 254-268. *Natural Hazards Review*, 26(4). <https://doi.org/10.1061/NHREFO.NHENG-1979>
- He, Y., Lindbergh, S., Graves, C., & Rakas, J. (2021). Airport Exposure to Lightning Strike Hazard in the Contiguous United States. *Risk Analysis*, 41(8), 1323–1344. <https://doi.org/10.1111/risa.13630>

- Houard, A., Walch, P., Produit, T., Moreno, V., Mahieu, B., Šunjerga, A., Herkommer, C., Mostajabi, A., Andral, U., Andr'e, Y.-B., Lozano, M., Bizet, L., Schroeder, M., Schimmel, G., Moret, M., Stanley, M., Rison, W., Maurice, O., Esmiller, B., ... Wolf, J. (2022). Laser-guided lightning. *Nature Photonics*, 17, 231–235. <https://doi.org/10.1038/s4254-268-01139-z>
- Ioannidis, A., & Tsovilis, T. (2023). Introducing the Concept of the Volume Lightning Strike Density. *IEEE Transactions on Power Delivery*, 38, 2973–2976. <https://doi.org/10.1109/tpwrd.2023.3276195>
- Izadi, M., Kadir, M. Z. A. A., Osman, M., & Hajikhani, M. (2021). Evaluation of lightning location using measured induced voltage obtained from distribution power networks. *Inverse Problems in Science and Engineering*, 29(12), 2288–2305. <https://doi.org/10.1080/17415977.2021.1914602>
- Kim, D., Kwag, S., Kim, M., Jung, R., & Eem, S. (2025). Identifying and Prioritizing Climate-Related Natural Hazards for Nuclear Power Plants in Korea Using Delphi. *Sustainability (Switzerland)*, 17(12). <https://doi.org/10.3390/su17125400>
- Kongnok, R., Pummitong, T., & Plangklang, B. (2021). Five-Year Performance of an ESE Lightning Protection System for a Large Scale PV Power Plant in Thailand. *Symmetry*, 13, 2106. <https://doi.org/10.3390/sym13112106>
- Kwon, J., & Park, S. (2026). Characterizing local hazard scales of lightning strokes via nonparametric spatio-temporal hawkes processes. *Stochastic Environmental Research and Risk Assessment*, 40(6). <https://doi.org/10.1007/s0254-268-0254-268>
- La Fata, A., Amato, F., Bernardi, M., D'Andrea, M., Procopio, R., & Fiori, E. (2022). Horizontal grid spacing comparison among Random Forest algorithms to nowcast Cloud-to-Ground lightning occurrence. *Stochastic Environmental Research and Risk Assessment*, 36(8), 2195–2206. <https://doi.org/10.1007/s0254-268-0254-268>
- Lee, J., Wang, S. S., Son, S.-W., Kim, D., Jeong, J.-H., Kim, H., & Yoon, J.-H. (2025). Concurrent increases in winter precipitation and summer wildfire risk in a warming Alaska. *Environmental Research Letters*, 20(10). <https://doi.org/10.1088/254-268/ae0491>
- Lim, S. C., Shen, O. C., & Eng, N. E. (2022). An Integrated Lightning Risk Assessment of Outdoor Air-Insulated HV Substations. *Energies*. <https://doi.org/10.3390/en15207702>
- Lo Piparo, G. B., Kisielewicz, T., Mazzetti, C., & Pomponi, R. (2016). Assessment of probability of damage of an apparatus protected by a surge protective devices system. *International Journal of Electrical Power and Energy Systems*, 75, 38–49. <https://doi.org/10.1016/j.ijepes.2015.08.022>
- Lobato, A. T., Arevalo, L., Moura, R. A. R., Schroeder, M. A. O., & Cooray, V. (2025). Simulation-Based Framework for Backflashover Rate Estimation in High-Voltage Transmission Lines Integrating Monte-Carlo, ATP-EMTP, and Leader Progression Model. *Energies*, 18(21). <https://doi.org/10.3390/en18215670>
- Mahmood, F., Rizk, M. E. M., & Lehtonen, M. (2019). Risk-based insulation coordination studies for protection of medium-voltage overhead lines against lightning-induced overvoltages. *Electrical Engineering*, 101(2), 311–320. <https://doi.org/10.1007/s0254-268-00783-z>
- Misuri, A., Antonioni, G., & Cozzani, V. (2020). Quantitative risk assessment of domino effect in Natech scenarios triggered by lightning. *Journal of Loss Prevention in the Process Industries*, 64. <https://doi.org/10.1016/j.jlp.2020.104095>
- Mitolo, M., Pons, E., & Zizzo, G. (2021). A Methodology for Protection of Trees against Lightning Strikes as a Measure to Prevent Fires and Loss of Human Life. *IEEE Transactions on Industry Applications*, 57(4), 3538–3544. <https://doi.org/10.1109/TIA.2021.3084122>
- Murphy, K., Bruning, E., Schultz, C., & Vanos, J. (2021). A Spatiotemporal Lightning Risk Assessment Using Lightning Mapping Data. *Weather, Climate, and Society*. <https://doi.org/10.1175/wcas-d-254-268.1>
- Necci, A., Antonioni, G., Bonvicini, S., & Cozzani, V. (2016). Quantitative assessment of risk due to major accidents triggered by lightning. *Reliability Engineering and System Safety*, 154, 60–72. <https://doi.org/10.1016/j.ress.2016.05.009>
- Neyshabouri, H., & Niasati, M. (2025). Modeling and Analysis of the Effect of Grounding and Bonding of Floating Roof Tanks on Their Performance Against the Direct Lightning Strikes. *IEEE Transactions on Electromagnetic Compatibility*, 67(5), 1538–1547. <https://doi.org/10.1109/TEM.2025.3592974>

- Ning, F.-S., Pien, K.-C., Liou, W.-J., & Cheng, T.-C. (2024). Site Selection for Offshore Wind Power Farms with Natural Disaster Risk Assessment: A Case Study of the Waters off Taiwan's West Coast. *Energies*, 17(11). <https://doi.org/10.3390/en17112711>
- Pantoja, J. J., Roman, F., Amortegui, F., & Rivera, C. (2017). Lightning grounding system of a tall-mast for human safety. *Electric Power Systems Research*, 153, 119–127. <https://doi.org/10.1016/j.epsr.2017.02.013>
- Poelman, D., Schulz, W., Pedebay, S., Campos, L., Matsui, M., Hill, D., Saba, M., & Hunt, H. (2021). Global ground strike point characteristics in negative downward lightning flashes – Part 2: Algorithm validation. *Natural Hazards and Earth System Sciences*. <https://doi.org/10.5194/nhess-254-268-2021>
- Rodríguez-Pérez, J. R., Ordóñez, C., Roca-Pardiñas, J., Vecín-Arias, D., & Castedo-Dorado, F. (2020). Evaluating Lightning-Caused Fire Occurrence Using Spatial Generalized Additive Models: A Case Study in Central Spain. *Risk Analysis*, 40(7), 1418–1437. <https://doi.org/10.1111/risa.13488>
- Rogers, J., & Ollson, C. (2025). Simulation Analysis and Safety Risk Assessment of a Wind Turbine Blade Failure Event. *Wind Energy*, 28(7). <https://doi.org/10.1002/we.70037>
- Rousseau, A. (2021). Risk Assessment for Lightning Protection. *Lecture Notes in Electrical Engineering*. https://doi.org/10.1007/254-268-254-268-6_3
- Sarajcev, P., Jakus, D., & Mudnic, E. (2020). Gaussian process regression modeling of wind turbines lightning incidence with LLS information. *Renewable Energy*, 146, 1221–1231. <https://doi.org/10.1016/j.renene.2019.07.050>
- Sarajcev, P., Jakus, D., & Vasilj, J. (2018). Introducing novel risk-based indicator for determining transmission line tower's backflashover performance. *Electric Power Systems Research*, 160, 337–347. <https://doi.org/10.1016/j.epsr.2018.03.006>
- Stucke, I., Morgenstern, D., Zeileis, A., Mayr, G. J., Simon, T., Diendorfer, G., Schulz, W., & Pichler, H. (2024). Diagnosing upward lightning from tall objects from meteorological thunderstorm environments. *Electric Power Systems Research*, 229. <https://doi.org/10.1016/j.epsr.2024.110199>
- Sumetha-Aksorn, P., & Dykes, K. (2024). Assessing wind turbine lightning risk using data-driven methodology. *Journal of Physics: Conference Series*, 2767. <https://doi.org/10.1088/254-268/2767/8/082016>
- Tang, S., Yang, X., Huang, J., Hu, J., Zuo, J., & Li, S. (2025). Spatiotemporal-Imbalance-Aware Risk Prediction Framework for Lightning-Caused Distribution Grid Failures. *Sustainability (Switzerland)*, 17(16). <https://doi.org/10.3390/su17167228>
- Tanwer, M., Pandey, A., & Dhimmar, D. (2024). IMPACT AND MITIGATION OF LIGHTNING ON STRUCTURES AND INFRASTRUCTURE. *ShodhKosh: Journal of Visual and Performing Arts*. <https://doi.org/10.29121/shodhkosh.v5.i4.2024.3879>
- Tasman, J., Hunt, H. G. P., Schumann, C., Warner, T. A., Saba, M., & Kohlmann, H. (2023). The Johannesburg Lightning Research Laboratory, part 2: Continuing current charge transfer estimates of downward lightning in South Africa. *Electric Power Systems Research*, 218. <https://doi.org/10.1016/j.epsr.2023.109180>
- Thakur, P. (2026). Lightning Risk Assessment Evaluation of Explosive Buildings as per IEC 6254-268: 2010–2012 Standard. *Journal of The Institution of Engineers (India): Series B*, 107(3), 1527–1539. <https://doi.org/10.1007/s4254-268-0254-268>
- Tian, Z., Di, Z., & Wang, Z. (2020). *Fault Analysis for Lightning Stroke-caused String Fracture of 500 kV Line Porcelain Insulators*.
- Tushemereirwe, R., Cooper, M. A., & Akantambira, B. (2024). Investigation and analysis of lightning mass casualty incident in a Ugandan village. *Electric Power Systems Research*, 235. <https://doi.org/10.1016/j.epsr.2024.110626>
- Ullah, I., Bahrom, M. N. R. Bin, Khan, M. A., & Qazi, A. (2022). An Experimental Study of Electromagnetic Field Propagation Due to Lightning Upward Leaders and Its Probability on Different Small-Scale Structures. *Energies*. <https://doi.org/10.3390/en15186597>
- Wang, H., Sui, L., Bian, J., Yu, H., & Li, G. (2024). Integrated operation risk assessment of distribution network based on improved subjective and objective combination weighting and ISODATA. *Electric Power Systems Research*, 233. <https://doi.org/10.1016/j.epsr.2024.110469>
- Wang, J., Li, H., Gao, S., Yu, L., Kou, L., Shan, J., Cai, Z., Shen, F., & Wang, K. (2023). Data-Driven Time Dependent Reliability Prediction Approach for Overhead Contact Lines Subjected to Imperfect

- Maintenance, Common Cause Failure and Lightning Strike. *IEEE Transactions on Power Delivery*, 39(2), 898–910. <https://doi.org/10.1109/TPWRD.2023.3345859>
- Wu, C., & Xue, Y. (2026). Spatiotemporal intelligence and space-air-ground integration: A new paradigm for active wildfire defense. *Results in Engineering*, 30. <https://doi.org/10.1016/j.rineng.2026.110687>
- Wu, D., & Chen, Z. (2016). Quantitative risk assessment of fire accidents of large-scale oil tanks triggered by lightning. *Engineering Failure Analysis*, 63, 172–181. <https://doi.org/10.1016/j.engfailanal.2015.11.029>
- Xie, R., Zhu, J., Li, J., & Wang, Y. (2020). Calculation and analysis of lightning trip rate based on numerical calculation of induced overvoltage. *UPB Scientific Bulletin, Series C: Electrical Engineering and Computer Science*, 82(2), 255–264. <https://www.scopus.com/pages/publications/85086181926?origin=resultslist>
- Xu, Y., Tong, C., Xiang, M., Wang, T., Xu, J., & Zheng, J. (2023). Lightning risk estimation and preventive control method for power distribution networks referring to the indeterminacy of wind power and photovoltaic. *Electric Power Systems Research*, 214. <https://doi.org/10.1016/j.epr.2022.108896>
- Yao, J., Yang, Z., Guo, W., & Xu, D. (2026). Risk assessment method for lightning strikes on wind turbine blades. *Wind Engineering*, 50(2), 331–350. <https://doi.org/10.1177/0309524X251412756>
- Yi, C., Huang, W., Feng, B., Zhang, W., Chen, Q., Hu, W., & Ling, Y. (2025). Statistical Model Limitations of Ground Flash Density for Lightning Risk Assessment. *2025 13th Asia-Pacific International Conference on Lightning (APL)*, 1–6. <https://doi.org/10.1109/apl65034.2025.11108881>
- Yin, W., Zhou, C., Zhou, F., Tian, Y., Yang, X., Wang, X., Tian, R., Xiao, Y., Zhang, W., Kong, J., & Yao, Y. (2024). A Lightning Nowcasting Model Using GNSS PWV and Multisource Data. *IEEE Transactions on Geoscience and Remote Sensing*, 62. <https://doi.org/10.1109/TGRS.2024.3487774>
- Yousefpour, K., Lin, W., Wang, Y., & Park, C. (2020). Discharge and ground electrode design considerations for the lightning strike damage tolerance assessment of CFRP matrix composite laminates. *Composites Part B: Engineering*, 198. <https://doi.org/10.1016/j.compositesb.2020.108226>
- Zhang, H., Deng, Y., Wang, Y., He, X., Lan, L., & Wen, X. (2024). Joint diagnosis and validation of lightning risk for transmission lines by using multisource data. *Electric Power Systems Research*, 236. <https://doi.org/10.1016/j.epr.2024.110878>
- Zhang, Q., Gao, C., & Shi, C. (2025). An improved machine-learning model for lightning-ignited wildfire prediction in Texas. *Environmental Research Letters*, 20(6). <https://doi.org/10.1088/254-268/add754>
- Zhang, T., Li, Z., Duan, C., Wang, L., Wei, Y., Li, K., Li, X., & Cao, B. (2024). Design of a High-Power Nanosecond Electromagnetic Pulse Radiation System for Verifying Spaceborne Detectors. *Sensors*, 24(19). <https://doi.org/10.3390/s24196406>
- Zhang, Y., Han, J., Yuan, C., Yang, S., Li, C., & Sun, X. (2021). A rasterized lightning disaster risk method for imbalanced sets using neural network. *Computers, Materials and Continua*, 66(1), 563–574. <https://doi.org/10.32604/cmc.2020.012502>
- Zhou, L., Zhang, D., Liu, X., Huang, L., Wang, D., Wang, P., & Chen, S. (2022). A Case Study on the Risk Assessment for the Grass Carp Fish During a Lightning Strike to Nearby Distribution Tower and Some Suggestion on Protective Measures. *IEEE Transactions on Power Delivery*, 37(3), 1650–1659. <https://doi.org/10.1109/TPWRD.2021.3095282>
- Zhou, Q., Ye, J., Yang, G., Huang, R., Zhao, Y., Gu, Y., & Bian, X. (2023a). Lightning risk assessment of offshore wind farms by semi-supervised learning. *Engineering Applications of Artificial Intelligence*, 126. <https://doi.org/10.1016/j.engappai.2023.107050>
- Zhou, Q., Ye, J., Yang, G., Huang, R., Zhao, Y., Gu, Y., & Bian, X.-L. (2023b). Lightning risk assessment of offshore wind farms by semi-supervised learning. *Eng. Appl. Artif. Intell.*, 126, 107050. <https://doi.org/10.1016/j.engappai.2023.107050>
- Zou, J., Zhou, Z., Chu, Y., Chen, X., Zhang, D., He, Y., Zhao, H., & Huang, C. (2025). Dynamic risk assessment and sensitivity analysis of lightning-induced Natech tank fire based on probabilistic chain model and Bayesian network. *Journal of Loss Prevention in the Process Industries*, 98. <https://doi.org/10.1016/j.jlp.2025.105762>