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Review

Radar Precipitation Uncertainty and Hydrological Applications: Mapping Topic Structure, Thematic Evolution, and Methodological Lineages Through Bibliometric and Transformer-Based Semantic Analysis

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Highlights

What are the main findings?

- Radar precipitation uncertainty research is structured around observation and correction, uncertainty and scale effects, hydrological propagation, and AI-driven forecasting.
- Statistical Fusion (36.2%) and Physics (17.4%) form the methodological foundation of the field, while AI (3.3%) and Hybrid methods (4.2%) represent emerging directions, with Hybrid methods bridging traditional and data-driven approaches.

What are the implications of the main findings?

- The field is shifting from product-level accuracy assessment toward chain-wide uncertainty representation linking precipitation observation, forecasting, hydrological response, and risk.
- Future research should integrate explainable AI, physical constraints, probabilistic modeling, and hydrological-response consistency to support risk-informed forecasting and decision-making.

Abstract

Radar precipitation information with high spatial and temporal resolution is essential for flood forecasting, urban pluvial flood warning, and digital twin basins, yet radar quantitative precipitation estimation (QPE) is affected by observational errors, retrieval relationships, terrain effects, and multi-source merging. Based on 1328 Web of Science Core Collection publications (2000–2025), this study integrates bibliometric analysis, Transformer-based semantic representation, BERTopic modeling, semantic association analysis, and bibliographic coupling to map the topic structure, thematic evolution, and methodological lineages of research on radar precipitation uncertainty and hydrological applications. Nineteen micro-level topics were identified and grouped into four categories: measurement error identification and correction, uncertainty characterization and modeling, error propagation and scale effects, and operational applications and risk decision-making. The semantic structure shows that observation and correction and hydrological propagation constitute the main branches, while AI-driven forecasting is emerging. Methodological lineage analysis indicates that Statistical Fusion dominates the field, Physics provides a foundation, and AI and Hybrid methods have grown markedly in recent years, with Hybrid methods

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bridging physical mechanisms, statistical fusion, and data-driven approaches. Future research should integrate explainable AI, physical constraints, probabilistic modeling, and hydrological-response consistency testing to advance chain-wide uncertainty representation from observation and forecasting to hydrological propagation and risk-informed decision-making.

Keywords: radar precipitation; quantitative precipitation estimation; uncertainty propagation; transformer-based semantics; BERTopic; methodological lineages; AI-physics fusion

1. Introduction

Under global climate change and the increasing occurrence of extreme precipitation events, riverine floods, urban pluvial flooding, and flash-flood hazards have created a growing demand for precipitation observations with high spatial and temporal resolution [1,2]. Convective precipitation often develops abruptly, shows strong local variability, and evolves rapidly. Conventional station-based observations therefore have limited capacity to capture its spatial structure and short-term evolution [3,4]. By contrast, new-generation weather radar can continuously monitor precipitation echoes at relatively high spatial and temporal resolution, making it an important data source for quantitative precipitation estimation, hydrological and hydrodynamic simulation, and flood forecasting and warning [5–7]. As digital twin basins and real-time forecasting systems continue to develop, transforming the observational advantages of radar into reliable digital representations of actual precipitation processes has become central to improving the timeliness of flood warnings and the scientific basis of risk-informed decision-making [8,9].

The reliability of radar precipitation information remains constrained by multiple sources of uncertainty [10,11]. Radar quantitative precipitation estimation (QPE) is influenced by electromagnetic wave propagation, particle scattering, and atmospheric microphysical processes. It is also affected by system calibration bias, ground clutter, attenuation correction, beam blockage, bright-band effects, and instability in the parameterization of Z–R relationships [12–14]. These errors do not remain at the observation stage. They enter hydrological models, hydrodynamic models, and risk assessment workflows through precipitation inputs, and they propagate nonlinearly across different spatial scales, temporal scales, and land-surface conditions [14,15]. The core issue in radar precipitation uncertainty research has therefore moved beyond improving the accuracy of a single QPE product. It now requires a fuller understanding of how errors are transmitted along the chain from observation, merging, and forecasting to hydrological response and risk assessment [16,17].

In recent years, the development of artificial intelligence (AI) methods has provided new technical pathways for radar precipitation estimation, nowcasting, and uncertainty correction [7,18,19]. Convolutional neural networks, recurrent neural networks, attention mechanisms, and deep generative models have shown strong capacity for nonlinear feature extraction, spatiotemporal sequence modeling, and multi-source information fusion. These methods have gradually been applied to radar precipitation retrieval, echo extrapolation, and convective precipitation forecasting [3,20]. At the same time, AI methods still face important limitations, including weak interpretability, dependence on training samples, limited cross-regional generalization, and insufficient physical consistency constraints [21,22]. Radar precipitation uncertainty research is therefore forming a new interdisciplinary frontier. This frontier combines the explanatory strengths of physical mechanisms and statistical fusion methods for identifying error sources with the representational capacity of AI methods for complex nonlinear processes.

Previous studies have discussed radar precipitation uncertainty from the perspectives of error sources, radar–gauge merging, data assimilation, hydrological error propagation, and ensemble flood forecasting [23,24]. However, the topic structure, evolutionary patterns, and methodological lineages of this field remain insufficiently characterized. Traditional reviews mainly rely on expert-based synthesis, which makes it difficult to identify latent semantic relationships and topic transition pathways in large literature collections. Conventional bibliometric analyses are usually based on keyword co-occurrence, author collaboration, or citation networks. These approaches provide valuable structural information, but they have limited ability to characterize the semantic continuity among research topics or to reveal the knowledge coupling among physics-based methods, statistical fusion methods, AI methods, and Hybrid methods [25–27]. It is therefore necessary to introduce semantic representation and topic modeling methods to systematically identify research topics, evolutionary pathways, and methodological differentiation in this field [28–30].

Using publications indexed in the Web of Science Core Collection from 2000 to 2025, this study develops a methodological framework that integrates Transformer-based semantic representation and BERTopic topic modeling to systematically identify the topic structure, evolutionary patterns, and methodological lineages of radar precipitation uncertainty research. In this study, the analysis of radar precipitation uncertainty centers on radar-derived precipitation information, with particular attention to uncertainty in multi-source precipitation merging, hydrological response propagation, flood forecasting and warning, and probabilistic risk expression. The scope covers radar QPE and its hydrological applications, as well as related topics in nowcasting and meteorological forecasting. The analysis maps the distribution, evolution, and interconnections of these research topics across the literature. This study addresses three questions: which core topics and high-level research categories constitute the field; how these topics evolved and aggregated during 2000–2025; and how physical mechanisms, statistical fusion, AI, and Hybrid methods have differentiated, interacted, and formed bridging relationships.

2. Data and Methods

2.1. Data Sources

The data used in this study were obtained from the Web of Science Core Collection (Clarivate, London, UK), covering the period 2000–2025. In accordance with the Web of Science indexing convention, records indexed as Early Access in 2025 were retained even when their final publication year was 2026. The retrieval and screening workflow is shown in Figure 1. The literature identification and screening process was documented using the PRISMA 2020 flow-diagram framework [31]. The review was not registered, and no separate review protocol was prepared. A two-stage hybrid retrieval strategy was used to construct the corpus for radar precipitation uncertainty research, with the aim of balancing literature coverage and topical relevance [32].

In the first stage, a topic-based search was conducted. The search query was designed around terms related to radar precipitation, including weather radar, radar precipitation, quantitative precipitation estimation, dual-polarization radar, and Z–R relationships. These terms were combined with application-context terms such as hydrology, basin, flood, runoff, and hydrometeorology to define the scope of the search. This stage was mainly used to cover studies related to radar precipitation estimation, bias correction, multi-source merging, and hydrological response analysis.

In the second stage, rule-based keyword screening and semantic similarity screening were conducted on the candidate records. Explicitly relevant publications were identified using domain keywords related to uncertainty, error, bias correction, ensemble, propagation, and data assimilation. For semantic screening, a pre-trained sentence embedding model

was used to encode titles and abstracts, and semantic similarity was calculated between each record and the core concepts of radar precipitation uncertainty and error propagation. The two screening approaches were combined using a logical OR rule, and records meeting either criterion were retained. A separate random sample of records was manually evaluated to assess screening performance; this validation procedure did not affect the composition of the final corpus [32–34].

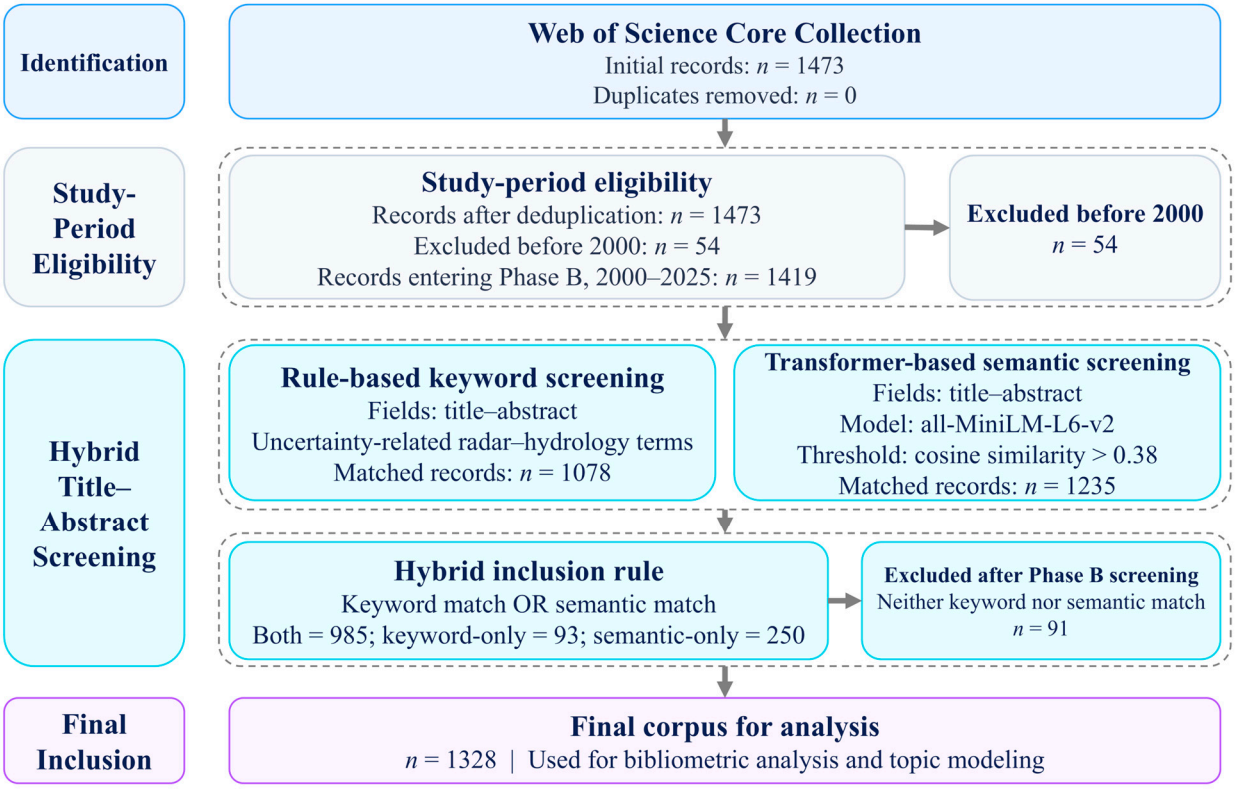


Figure 1. Two-stage literature retrieval and screening workflow. Note: Blue boxes represent literature identification and eligibility screening, cyan boxes represent hybrid keyword-based and semantic screening, and purple boxes indicate final inclusion. Gray dashed outlines group related screening procedures, while arrows indicate the workflow sequence.

The first-stage search returned 1473 records. After removing 54 records published before 2000, 1419 records were retained for subsequent screening. Through the hybrid rule-based and semantic screening procedure, 91 records that did not meet either screening criterion were excluded. A final set of 1328 publications was retained for subsequent bibliometric analysis and topic modeling. The complete identification, screening, eligibility, and inclusion process is summarized in the PRISMA 2020 flow diagram (Figure S1). The full list of the 1328 publications included in the review corpus is provided in Supplementary Table S1.

2.2. Semantic Topic Modeling

To identify the latent topic structure of radar precipitation uncertainty research, this study developed a semantic topic modeling workflow centered on BERTopic, as shown in Figure 2. BERTopic combines Transformer-based semantic embeddings, clustering analysis, and c-TF-IDF topic representation, allowing interpretable topic structures to be extracted from short texts such as article abstracts [35–37].

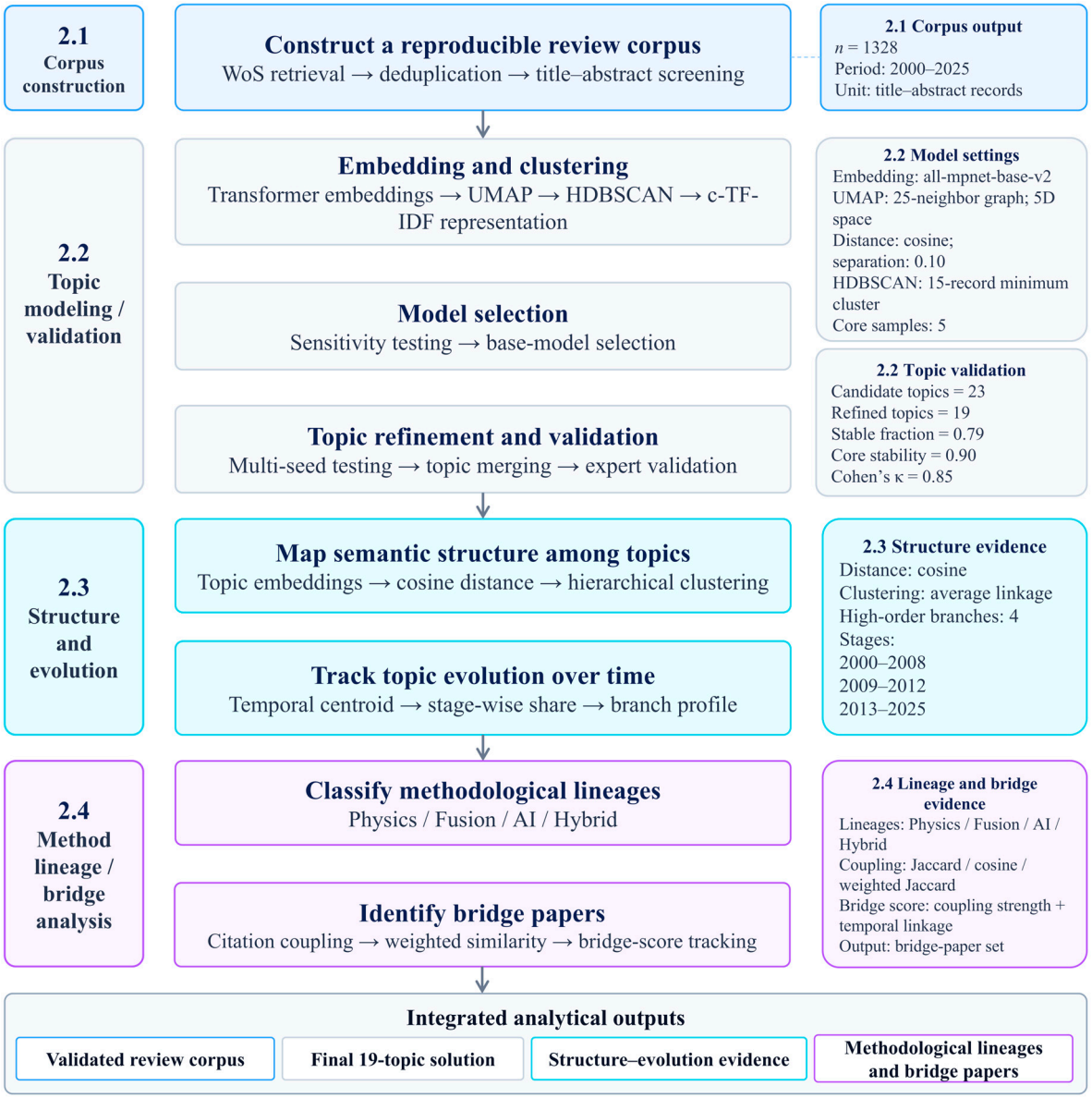


Figure 2. Overall methodological framework. Note: Blue, gray, cyan, and purple panels represent corpus construction, topic modeling and validation, topic structure and evolution analysis, and methodological lineage and bridge analysis, respectively. The three publication-development stages reflect descriptive changes in annual publication counts and their three-year moving average, as described in Section 3.1.1.

In the topic generation stage, the screened titles and abstracts were used as input. Semantic embeddings were generated using the sentence-transformers/all-mpnet-base-v2 model, and semantically similar document clusters were identified by combining UMAP and HDBSCAN. For UMAP, the parameters were set as n_neighbors = 25, n_components = 5, and min_dist = 0.10, with cosine distance used as the metric. For HDBSCAN, min_cluster_size was set to 15, min_samples to 5, and cluster_selection_method to leaf. The representative terms of each topic were then extracted using c-TF-IDF, and standardized topic labels were generated through manual semantic verification [29,38].

To assess the stability of the final 19-topic framework, we conducted 38 clustering runs using the same corpus of 1328 publications and fixed document embeddings, including one baseline reproduction, ten random-seed runs, and 27 single-parameter perturbation runs. Following outlier reassignment and semantic alignment, the clustering results were

mapped onto a fixed 19-topic reference framework. Using a document-set Jaccard similarity threshold of 0.50 and requiring this criterion to be satisfied in at least 80% of the runs within each test group, 15 and 14 of the 19 topics met the seed-stability and parameter-perturbation stability criteria, respectively. Across the random-seed runs, the adjusted Rand index (ARI) ranged from 0.686 to 0.765, and normalized mutual information (NMI) ranged from 0.792 to 0.830. These results indicate that most reference topics were recoverable under the tested conditions, although some remained sensitive to parameter settings. The additional stability analyses were conducted using Python 3.12.1, BERTopic 0.17.4, Sentence Transformers 5.2.0, umap-learn 0.5.11, and hdbscan 0.8.41. The embedding model was sentence-transformers/all-mpnet-base-v2, with the model revision fixed at e8c3b32edf5434bc2275fc9bab85f82640a19130.

Based on the model outputs, this study further combined topic keywords, representative publications, topic similarity, and expert interpretation to merge semantically similar or overlapping topics and refine their labels. The 19 topics were grouped into four high-level research categories—measurement error identification and correction, uncertainty characterization and modeling, error propagation and scale effects, and operational applications and risk decision-making—as shown in Table 1. The classification process was independently verified by two experts using a unified coding scheme [34,39]. Cohen's κ was 0.85, indicating a high level of agreement. The normalized topic labels are provided in Appendix A Table A1.

For example, pre-merge BERTopic topic 5 comprises 41 publications on radar–gauge rainfall merging. This topic was retained without merging and reindexed as final topic T14. Automatic keyword processing retained "merging", "gauge", "radar", "rain", and "data". Representative publications in the retained model outputs include Huang et al. (2023), Seck and Van Baelen (2018), and Le et al. (2025) [40–42]. Their abstracts describe kriging-based integration of radar and gauge observations and comparisons of statistical and geostatistical merging methods. These keywords and publications support the standardized label "Geostatistical radar-gauge merging" in Appendix A Table A1. Expert semantic judgment links the keyword–publication correspondence to the shared research problem and guides scientific label interpretation.

Table 1. High-level research categories and methodological characteristics.

High-Level Research Category	Core Focus	Representative Methods and Metrics
Measurement error identification and correction	Error-source identification; calibration bias and attenuation effects; instability of Z–R relationships; multi-source merging correction [10,11]	Quality control; error decomposition and bias correction; error tracking; bias, RMSE, correlation coefficient
Uncertainty characterization and modeling	Uncertainty features of residual errors after correction; error distribution and stochastic structure characterization; ensemble representation; uncertainty propagation in data assimilation [43]	Random fields; ensemble simulation; Bayesian inference; probability distributions; confidence intervals; posterior ensembles
Error propagation and scale effects	Propagation of precipitation-input errors into hydrological processes; temporal-scale effects; spatial-scale effects; watershed response differences [44]	Scale comparison experiments; sensitivity analysis; error attribution; runoff-response bias; volumetric error
Operational applications and risk decision-making	Translation of uncertainty information into forecasting, warning, and risk management; probabilistic product generation; threshold triggering; decision support [4,45,46]	Ensemble-driven forecasting; exceedance probability estimation; risk assessment; warning probability; decision-support indicators

2.3. Semantic Association Analysis

Based on the micro-level topic identification results, this study further characterized the semantic proximity relationships within the field [47,48]. This procedure corresponds to the Structure and evolution module in Figure 2.

Specifically, the standardized topic names, representative terms, and representative publication fragments of each topic were extracted to construct topic-level semantic description texts. A pre-trained Sentence Transformer model was then used to generate topic embeddings, and cosine distance was used to measure semantic differences among topics, resulting in a topic semantic distance matrix [44,49]. This matrix was used to characterize the relative distances among micro-level topics and provided the basis for subsequent identification of topic proximity relationships and higher-order semantic branches.

To reveal the aggregation structure of topics in the semantic space, this study used agglomerative hierarchical clustering with average linkage to identify topic aggregation relationships [50]. After comparing solutions with different numbers of branches, four higher-order semantic branches were finally determined by jointly considering branch size, within-branch semantic coherence, between-branch separation, and domain interpretability [47]. The naming and interpretation of each branch were based on topic names, keywords, representative publications, and domain knowledge. These branches were used to explain the relationships among different topics in observation, correction, propagation, and forecasting.

To assess the practical relevance of the identified research topics, this study compared topic popularity with the operational forecasting and warning functions of six representative systems: NOAA in the United States, China MWR, JMA in Japan, EFAS in Europe, FFC/Met Office in the United Kingdom, and BoM in Australia. Based on publicly documented operational functions and the standardized labels, representative keywords, and research content of the 19 topics, topic–system relationships were classified as Direct, Indirect, or Not established. Direct indicated alignment between a topic's general research objective and a documented operational task, while Indirect indicated a related supporting function. Not established indicated insufficient evidence of task-level alignment in the available descriptions. This classification characterizes thematic relevance at the operational-task level.

2.4. Methodological Lineages and Bridge Identification

To characterize the development pathways of radar precipitation retrieval, correction, and forecasting research from a methodological perspective, this study constructed a methodological lineage classification framework. This procedure corresponds to the Method lineage/bridge analysis module in Figure 2 [51,52]. Using a predefined keyword dictionary applied to publication titles and abstracts, the studies were classified into five categories: Physics, Statistical Fusion, AI, Hybrid, and Other [21,25,53,54].

Physics focuses on dual-polarization observations, microphysical processes, radar-variable relationships, and error mechanisms. Statistical Fusion focuses on radar–gauge merging, bias correction, geostatistical interpolation, and multi-source precipitation merging. AI focuses on machine learning and deep learning models. Hybrid encompasses cross-lineage methodological integration, including the combination of data-driven methods with physical constraints, radar-variable information, or statistical-fusion techniques. The keyword-based classification prioritized Hybrid when hybrid-specific terms were detected or AI keywords co-occurred with Physics or Statistical Fusion keywords. Otherwise, primary categories were assigned in the order of AI, Statistical Fusion, and Physics, with unmatched publications assigned to Other. Additional matched categories were retained as secondary labels. To evaluate classification agreement, a stratified sample of 132 publications (9.9% of the full corpus) was selected from the four core methodological categories

for manual validation. The manual labels were used for evaluation, while the automatic labels were retained for subsequent methodological-lineage analyses [55].

To assess the sensitivity of methodological evolution to classification choices, this study conducted a rule-based scenario analysis following the principle of evaluating robustness across alternative coding decisions [56]. Four scenarios were considered: S0 retained the original five-category classification; S1 focused on the four core methodological lineages; S2 applied strict rules requiring explicit evidence of method implementation within Other; and S3 employed expanded rules to identify additional methodological signals. The screening used predefined terms, regular expressions, and contextual criteria applied to titles, abstracts, author keywords, and Keywords Plus, with textual evidence interpreted according to its methodological role [57]. Publications with ambiguous assignments across multiple lineages retained their Other labels. Category sizes, temporal characteristics, and weighted reference coupling were compared across scenarios using a common citation-weighting framework.

To analyze knowledge connections among different methodological lineages, this study further conducted coupling and bridge identification based on citation information [58]. Reference sets were constructed using a combined strategy that prioritized DOI matching and incorporated exact title matching and fuzzy title matching [51]. Jaccard index, cosine similarity, and weighted Jaccard index were then used to measure coupling strength among methodological lineages [59]. For bridge identification, Physics and Statistical Fusion were merged into a traditional physics–statistics knowledge source pool, while AI and Hybrid were merged into an AI-related candidate set. Cross-lineage bridging publications were then identified according to reference overlap and weighted similarity between the two groups [25,60]. Hybrid publications were included both as a methodological lineage in the overall structural analysis and as an important component of the bridge-candidate set for identifying cross-lineage knowledge connections [61].

To select representative bridging publications, this study considered bridging scores, reference overlap, weighted similarity, topic relevance, and bibliographic quality, and then confirmed the representative publications through manual review. The final selection balanced bridging strength, topic coverage, and method type. The selected publications were used to illustrate how AI and Hybrid methods have been embedded into the existing physics–statistics knowledge system through radar precipitation estimation, error correction, multi-source merging, and hydrological response problems.

3. Results

3.1. Research Evolution Trends

3.1.1. Annual Publications and Source Distribution

Figure 3a,b show the annual number of publications and the three-year moving average from 2000 to 2025, as well as the annual contribution matrix of the top 10 journals. The annual publication output shows distinct phases. During 2000–2008, related studies remained at a low and fluctuating level, with most years producing approximately 20–30 publications. After 2009, the number of publications increased markedly and reached 95 in 2012. Since 2013, annual output has remained relatively stable at a high level, with most years ranging between 60 and 80 publications. The three-year moving average further indicates that 2009–2012 was the most concentrated period of publication growth. After 2013, annual output remained high, although interannual fluctuations became more pronounced.

In terms of journal sources, the publications were concentrated in several leading journals. Journal of Hydrology made the largest contribution, with 158 publications, followed by Journal of Hydrometeorology and Hydrology and Earth System Sciences, with 94 and 61 publications, respectively. The remaining journals mainly contributed between 25 and

47 publications. This pattern indicates that research in this field has mainly been published in journals related to hydrology, hydrometeorology, remote sensing, water resources, and atmospheric sciences. In terms of temporal distribution, Journal of Hydrology, Journal of Hydrometeorology, and Hydrology and Earth System Sciences maintained continuous contributions throughout the study period. The contributions of Water and Remote Sensing mainly appeared after 2010 and became more concentrated during 2018–2025.

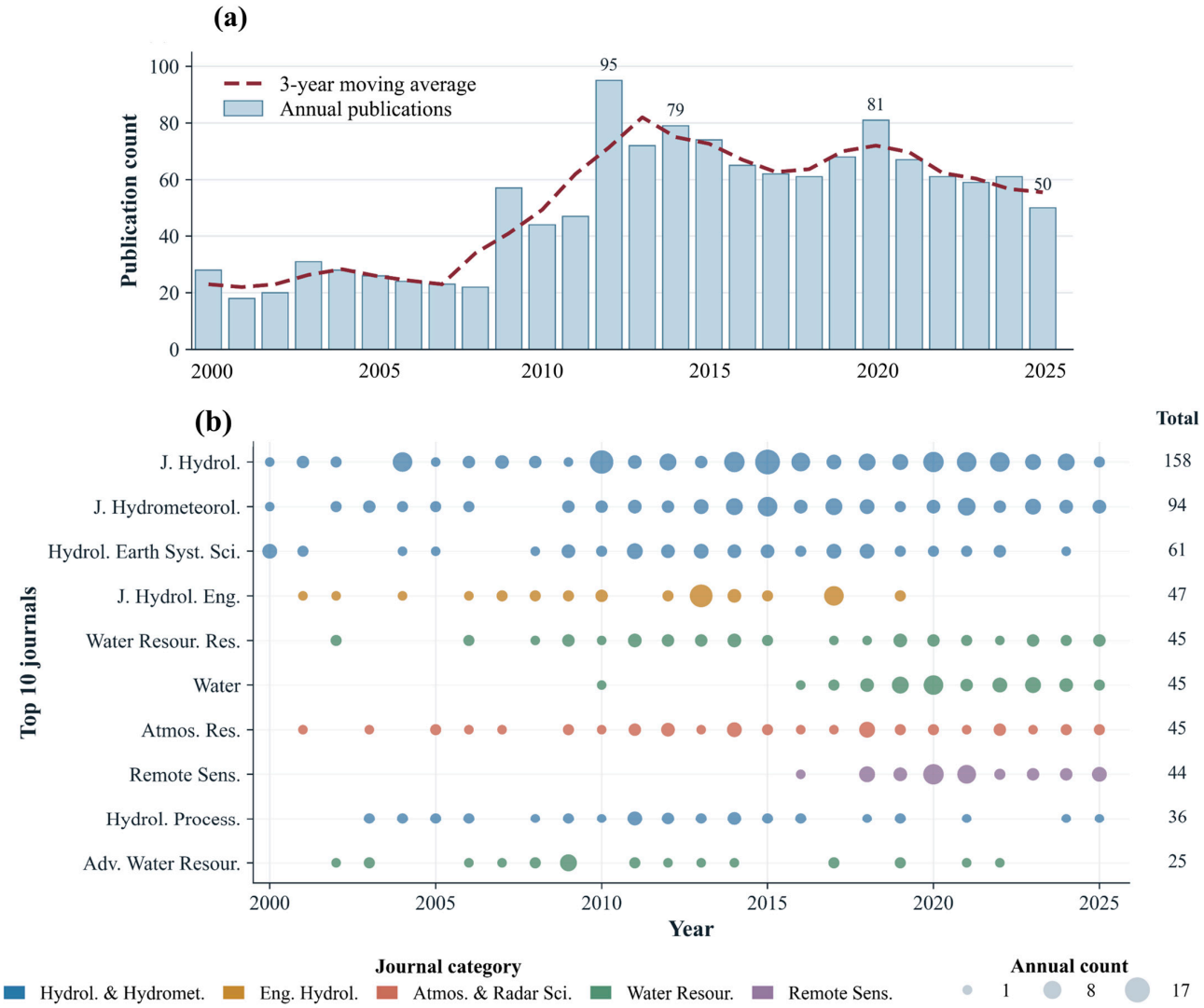


Figure 3. Annual publication output and journal contribution matrix: (**a**) Annual number of publications and three-year moving average from 2000 to 2025. (**b**) Annual contributions of the top 10 journals; bubble size represents the annual number of publications, and color represents journal category.

Overall, radar precipitation uncertainty research entered a phase of rapid development after 2009 and subsequently maintained a relatively stable level of publication output. The journal sources are dominated by hydrology and hydrometeorology journals, while the contributions of remote sensing and integrated water-science journals increased in the later period.

3.1.2. International Collaboration Patterns

Figure 4a–c show the geographical distribution, collaboration link strength, and international collaboration rate of radar precipitation uncertainty research from 2000 to 2025, respectively. Research output was mainly concentrated in North America, East Asia, and

Europe. The USA and China had the largest publication outputs, while European countries showed a denser geographical distribution.

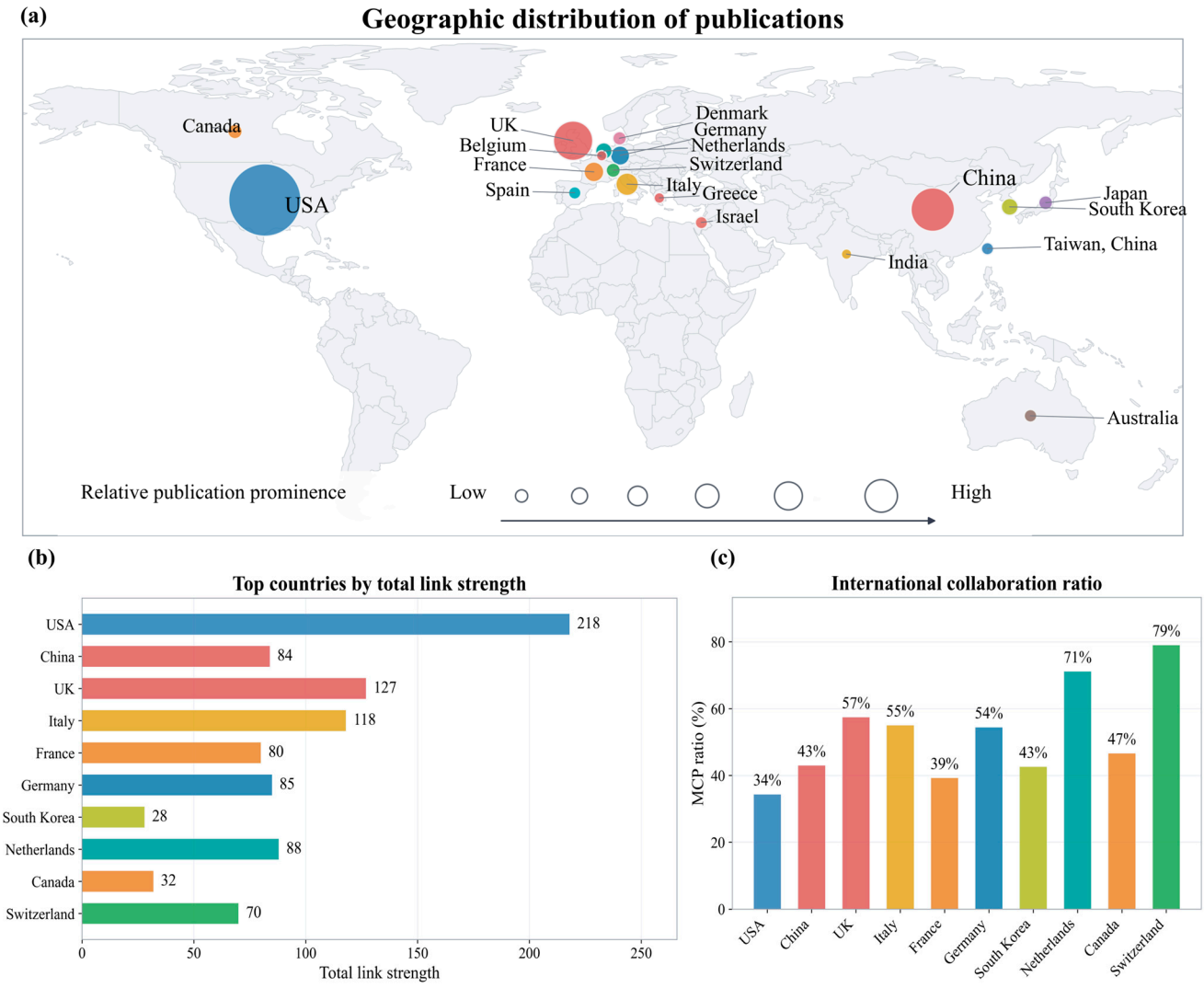


Figure 4. Geographical distribution and international collaboration patterns: (**a**) Geographical distribution of publications. (**b**) Countries with the highest total link strength. (**c**) International collaboration rate, expressed as the proportion of multi-country publications (MCP).

In terms of collaboration links, the USA had the highest total link strength, followed by the UK and Italy. The Netherlands, Germany, China, France, and Switzerland showed intermediate levels of link strength. The MCP rate reflects the proportion of multi-country publications in a country's total publication output. Switzerland and the Netherlands had the highest MCP rates, at 79% and 71%, respectively. The UK, Italy, and Germany also maintained relatively high MCP rates, at 57%, 55%, and 54%, respectively. By contrast, the MCP rates of the USA and China were 34% and 43%, respectively, which were lower than those of most European countries.

Overall, publication volume and international collaboration rate were not fully aligned. The USA occupied a central position in both publication output and collaboration link strength, but its proportion of multi-country publications was relatively low. European countries had more limited single-country publication outputs, but their cross-national collaboration was more active. China had a high publication output, while its collaboration link strength and MCP rate were lower than those of several European countries.

3.2. Topic Structure and Category Evolution

3.2.1. Topic Distribution and Evolution

To analyze the topic structure and evolutionary patterns of radar precipitation uncertainty research, this study identified 19 micro-level topics based on the BERTopic results after post-processing and merging. These topics were numbered T0–T18. Their full names, core keywords, temporal centroids, and representative publications are provided in Appendix A Tables A1 and A2. Figure 5a,b show the temporal changes in the relative share of each topic from 2000 to 2025 and the top five topics with the highest pooled publication shares in each stage, respectively. For the descriptive analysis, the stage boundaries were selected based on annual publication counts and their three-year moving average, as presented in Section 3.1.1: Stage I (2000–2008), Stage II (2009–2012), and Stage III (2013–2025).

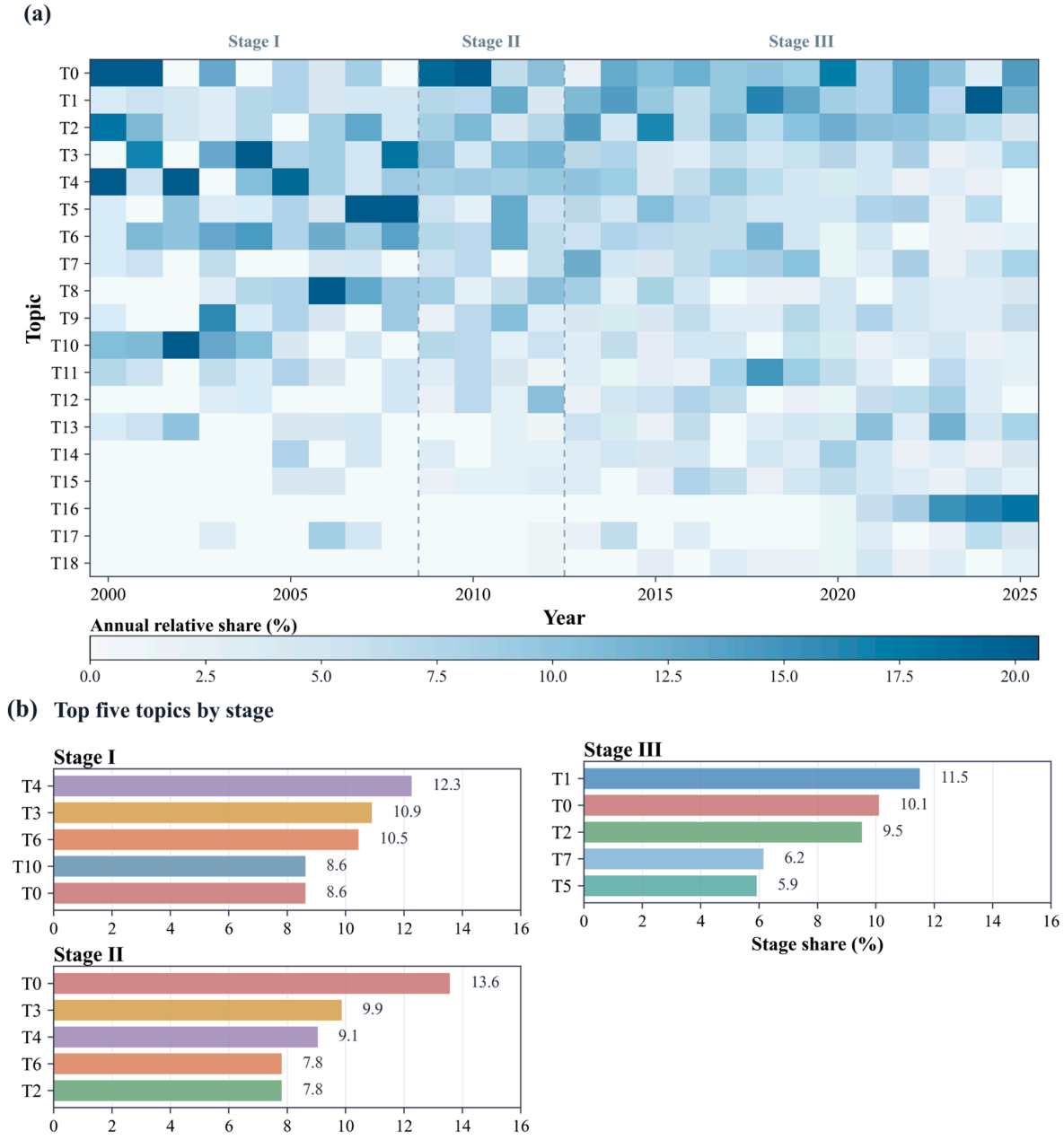


Figure 5. Changes in relative topic shares across different periods: (**a**) Heatmap of annual relative topic shares from 2000 to 2025. (**b**) Top five topics ranked by pooled publication share within each stage. Note: Stage share is calculated as the number of publications assigned to a topic divided by the total number of publications in that stage. Full topic names are provided in Appendix A Table A1.

During Stage I, the topics with relatively high pooled publication shares were T4, T3, T6, T10, and T0. Early studies mainly focused on radar–gauge correction, hydrological simulation, rainfall error identification, and flash-flood response. During Stage II, T0, T3, T4, T6, and T2 accounted for relatively high shares, indicating that flash-flood response, hydrological simulation, observation correction, and dual-polarization radar precipitation estimation were the main research directions. During Stage III, T1, T0, T2, T7, and T5 became more prominent, and research further concentrated on satellite precipitation estimation, flash-flood response, dual-polarization radar estimation, urban flood response, and radar precipitation estimation. Meanwhile, the shares of T16 and T18 increased after 2020, suggesting that deep-learning-based precipitation forecasting and CML rainfall retrieval have emerged as rapidly growing research directions. Across the three stages, the thematic focus gradually expanded from observation correction and error identification to multi-source estimation, hydrological response, and intelligent prediction.

Temporal centroids reflect the temporal concentration of research activity, while annual publication counts and topic proportions further reveal shifts in research attention and emerging trends. Topics with earlier temporal centroids were mostly associated with foundational issues, including radar precipitation estimation, error identification, radar–gauge correction, and traditional hydrological simulation. Mid-stage topics reflected directions such as multi-source merging, geostatistical merging, and hydrological process simulation. Topics with later temporal centroids were concentrated in emerging directions, including CML rainfall retrieval, deep-learning-based precipitation forecasting, flood response, and intelligent modeling. Overall, radar precipitation uncertainty research has gradually evolved from early observation-side error assessment into an integrated knowledge system covering multi-source merging, error propagation, hydrological response, and intelligent prediction.

3.2.2. Mapping Topics to High-Level Research Categories

This section further maps the micro-level topics onto high-level research categories, as shown in Figure 6. Overall, measurement error identification and correction contains the largest number of topics, with nine topics assigned to this category. Error propagation and scale effects includes six topics, whereas uncertainty characterization and modeling and operational applications and risk decision-making contain the fewest topics, with two topics each. This result indicates that current research remains dominated by observational error identification, data correction, and hydrological impact analysis. Explicit uncertainty modeling and probabilistic risk expression for operational applications remain relatively underdeveloped.

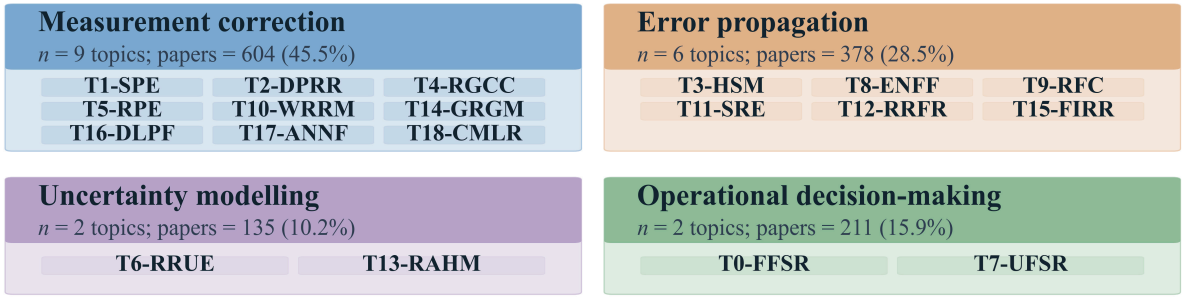


Figure 6. Mapping of topics to high-level research categories. Note: Full topic names are provided in Appendix A Table A1.

In terms of specific mapping relationships, measurement error identification and correction includes T1, T2, T4, T5, T10, T14, T16, T17, and T18. These topics cover satellite precipitation estimation, dual-polarization radar observation, radar–gauge correction, multi-

source merging, weather-radar rainfall modeling, and AI-assisted precipitation estimation. Uncertainty characterization and modeling includes T6 and T13, mainly involving radar precipitation errors, uncertainty representation, data assimilation, and related modeling issues. Error propagation and scale effects includes T3, T8, T9, T11, T12, and T15, linking hydrological simulation, rainfall–flood coupling, ensemble forecasting, spatial-resolution effects, and flood-inundation response. Operational applications and risk decision-making includes T0 and T7, reflecting application-oriented issues such as the spatiotemporal response of flash floods, urban flooding, and drainage-system response.

The field has formed a research chain that includes observational error identification and correction, uncertainty characterization, hydrological propagation analysis, and risk-oriented applications. However, the topic distribution shows that the two ends of this chain are unevenly developed. Observation correction and error propagation dominate the field, while explicit uncertainty modeling and operational risk expression remain insufficient. This finding provides a basis for the subsequent discussion of the shift from product-accuracy evaluation toward chain-based uncertainty representation.

3.3. Topic Proximity Relationships and Hierarchical Structure

3.3.1. Semantic Proximity Relationships Among Topics

To reveal semantic proximity relationships among different topics in radar precipitation uncertainty research, this study calculated pairwise topic distances based on topic semantic vectors and further conducted hierarchical clustering analysis. Figure 7a,b show the topic hierarchical clustering results and the pairwise topic distance matrix, respectively. The former was used to identify topic merging pathways and local cluster structures, while the latter was used to present the degree of semantic proximity among topics. Figure 7a shows that the 19 micro-level topics form several interconnected branches in the hierarchical clustering tree. The topics exhibit strong semantic continuity, and topics related to measurement error correction, uncertainty modeling, error propagation, and operational applications show cross-category merging relationships at several clustering nodes.

In Figure 7b, lighter areas indicate smaller semantic distances and stronger topic proximity, whereas darker areas indicate greater semantic separation. The matrix can be summarized into three relatively stable local topic clusters. C1 represents the close connection among hydrological simulation, operational applications, and risk response, and can be regarded as a hydrological–operational linkage cluster. C2 is located in the central part of the matrix and covers a broader range of topics. It mainly reflects core issues related to radar precipitation estimation, error identification, bias correction, data merging, and scale adjustment, and can be regarded as a radar-correction core cluster. C3 connects quantitative precipitation forecasting, ensemble forecasting, spatiotemporal extrapolation, and uncertainty transmission, and can be regarded as a forecasting bridge cluster.

Overall, Figure 7 reveals the hierarchical relationships among the correction core, forecasting bridge, and hydrological–operational linkage. C1–C3 mainly reflect local proximity clusters in the topic semantic distance matrix and are used to explain the relative closeness among micro-level topics. Radar precipitation error correction constitutes an important knowledge center in this field. Forecasting-related topics connect estimation uncertainty with future risk warning, while hydrological propagation and operational decision-making topics reflect the extension of the knowledge system toward applications.

3.3.2. Topic Structure and Higher-Order Aggregation

Based on the topic semantic distance matrix and hierarchical clustering results, the 19 micro-level topics were further aggregated into four higher-order semantic branches—observation and correction (B1), uncertainty and scale effects (B2), hydrological prop-

agation (B3), and AI-driven forecasting (B4)—as shown in Figure 8. C1–C3 in Figure 7 mainly show local proximity relationships among micro-level topics and reflect their relative closeness in the topic semantic distance matrix. By contrast, B1–B4 in Figure 8 provide a higher-order summary of the topic structure by combining hierarchical clustering results with domain interpretation. Table 2 summarizes the number of topics, publication volume, publication share, dominant role, and representative topics of each higher-order branch.

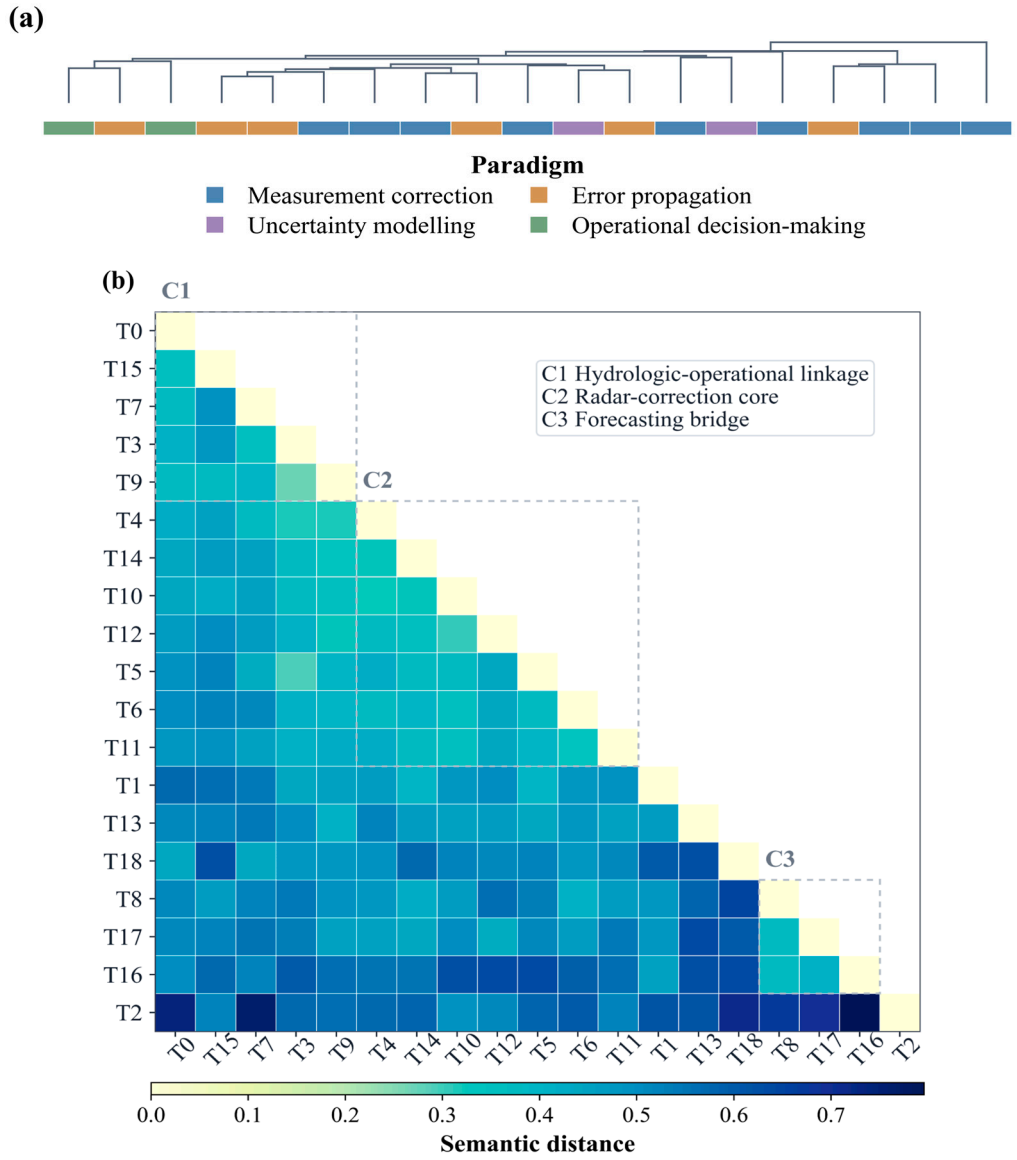


Figure 7. Hierarchical semantic proximity and clustering-distance structure of topics: (**a**) Hierarchical clustering dendrogram of the 19 micro-level topics. (**b**) Lower-triangular semantic distance matrix among topics, ordered according to the hierarchical clustering results. Note: Gray dashed outlines indicate the three local topic proximity clusters (C1–C3) highlighted in the semantic distance matrix. Full topic names are provided in Table A1 in Appendix A.

The results show that B1 and B3 are the two main branches of the field. B1 contains seven topics and 542 publications, accounting for 40.8% of the corpus. This branch mainly corresponds to radar precipitation estimation, observation correction, and multi-source precipitation information acquisition. B3 contains seven topics and 518 publications, accounting for 39.0% of the corpus. It mainly corresponds to hydrological simulation, flood response, urban flooding, and inundation analysis. B2 contains two topics and 140 publications, accounting for 10.5% of the corpus, and mainly involves rainfall error, uncertainty,

and spatial-resolution effects. B4 contains three topics and 128 publications, accounting for 9.6% of the corpus, and mainly corresponds to intelligent forecasting directions such as deep learning, artificial neural networks, and ensemble nowcasting.

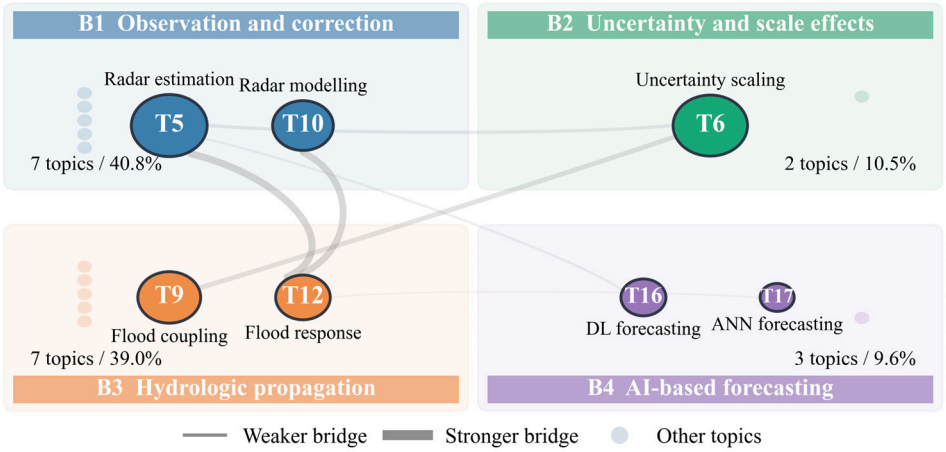


Figure 8. Hierarchical clustering structure and higher-order semantic branches of topics.

Table 2. Composition, publication share, and representative topics of higher-order branches.

Branch	Topics	Documents/Share	Dominant Role	Representative Topics
B1 Observation and correction	7	542/40.8%	Measurement correction	T1, T2, T4, T5, T10, T14, T18
B2 Uncertainty and scale effects	2	140/10.5%	Uncertainty scaling	T6, T11
B3 Hydrologic propagation	7	518/39.0%	Hydrologic response	T0, T3, T7, T9, T12, T13, T15
B4 AI-based forecasting	3	128/9.6%	Forecasting decisions	T8, T16, T17

Note: Full topic names are provided in Appendix A Table A1. Higher-order branches were determined jointly based on topic similarity evidence and manual semantic merging. Representative topics are used to describe the main semantic composition of each branch and do not indicate strictly mutually exclusive research boundaries.

Figure 8 further shows that the semantic connection between B1 and B3 is the most prominent, indicating a close relationship between observation-estimation and correction topics and hydrological propagation topics. T5 and T10 in B1 represent radar precipitation estimation and weather-radar rainfall modeling, while T9 and T12 in B3 represent rainfall–flood coupling and radar-precipitation-driven flood response. The strong connection between these topics highlights the effects of radar precipitation errors on flood simulation and response analysis as a key link between observational and hydrological research. T6 in B2 is connected to both B1 and B3, suggesting that uncertainty and scale effects play a mediating role between observation correction and hydrological propagation. T16 and T17 in B4 have entered the higher-order semantic structure, but their connections with B1 and B3 remain relatively weak. This indicates that AI forecasting topics are expanding, while their links with traditional observation correction and hydrological propagation topics still need to be strengthened.

Overall, radar precipitation uncertainty research is dominated by observation correction and hydrological propagation, with uncertainty and scale effects and AI-driven forecasting serving as complementary branches. This structure shows that current research

focuses on radar precipitation estimation and error correction, while also strengthening its application links with flood response, urban flooding, and intelligent forecasting.

3.4. Cross-Lineage Analysis and Identification of Bridging Publications

3.4.1. Methodological Lineage Structure and Evolution

This section examines the structure, temporal evolution, and cross-lineage connections of the methodological approaches used in radar precipitation uncertainty research. Table 3 presents the publication volume and temporal centers of different methodological lineages. Figure 9a–c show the annual changes in methodological lineages, the distribution of temporal centers and publication volumes, and cross-lineage coupling relationships, respectively.

Table 3. Publication volume and temporal centers of methodological lineages.

Method Lineage	Number of Papers	Mean Publication Year	Median Publication Year
Physics	231	2014.3	2014.0
Statistical Fusion	481	2015.0	2016.0
AI	44	2020.3	2023.5
Hybrid	56	2019.8	2022.0
Other	516	2014.0	2014.0

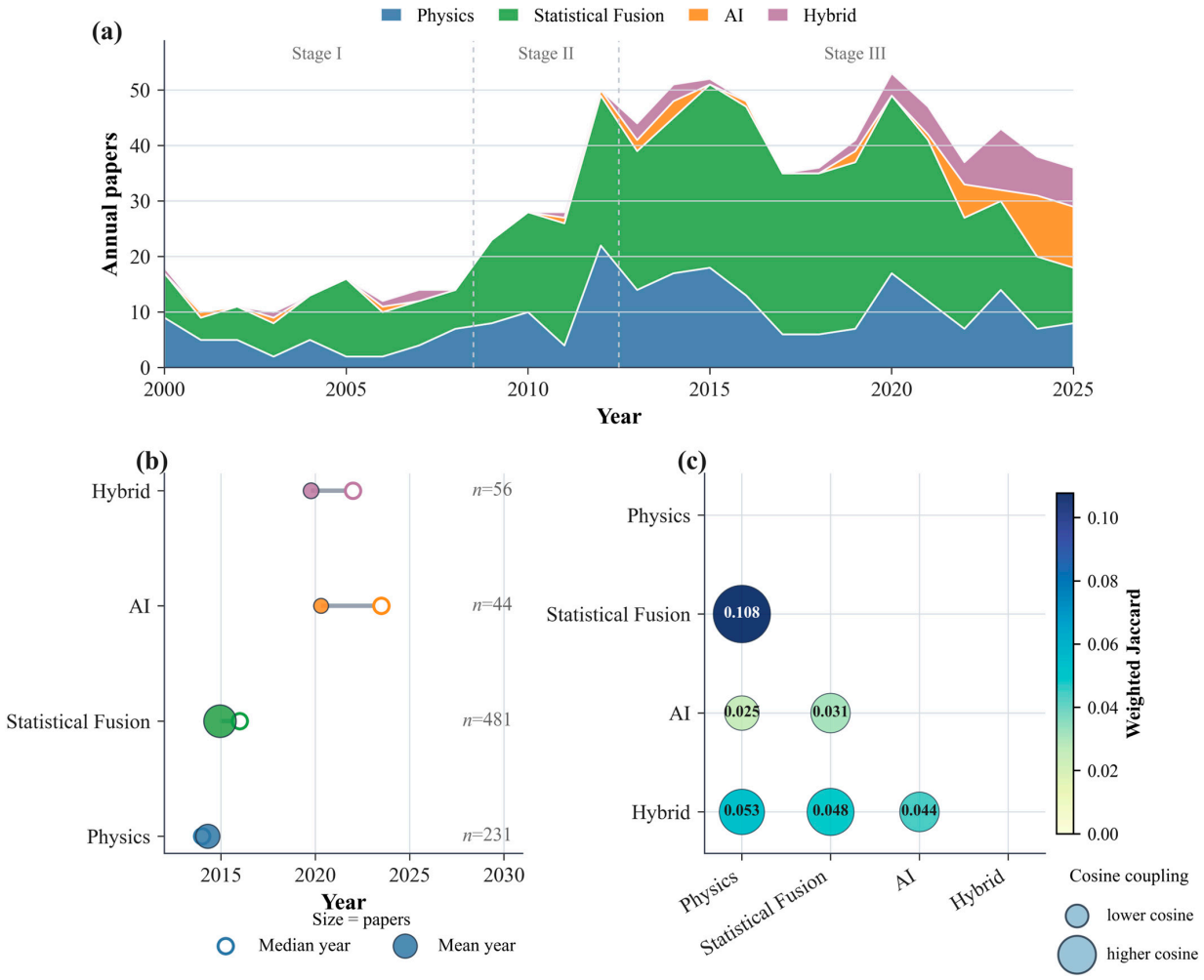


Figure 9. Evolution, temporal centers, and cross-lineage coupling of methodological lineages: (**a**) Annual evolution of methodological lineages. (**b**) Temporal centers and publication volumes of methodological lineages. (**c**) Cross-lineage coupling matrix.

Table 3 shows that, among the four core methodological lineages, Statistical Fusion contains the largest number of publications, with 481 records. Physics includes 231 publications, while AI and Hybrid are smaller in scale, with 44 and 56 publications, respectively. In terms of temporal centers, the mean and median publication years of AI are 2020.3 and 2023.5, respectively, while those of Hybrid are 2019.8 and 2022.0, respectively. These values are clearly later than those of Physics and Statistical Fusion, indicating that data-driven methods and hybrid methods are mainly concentrated in recent publications.

Figure 9a shows that Physics and Statistical Fusion appeared in the early stage of the field. Statistical Fusion increased markedly after Stage II and accounted for a relatively high proportion in most years. Physics had a smaller publication volume than Statistical Fusion, but it was present throughout the study period. The proportions of AI and Hybrid increased after 2020 and became more prominent after 2022, suggesting that data-driven methods and their integration with traditional methods have become new sources of methodological growth.

Figure 9b further shows that the mean and median publication years of Physics and Statistical Fusion are relatively early, whereas the temporal centers of AI and Hybrid shift distinctly toward more recent years. Figure 9c indicates that the cross-lineage coupling between Physics and Statistical Fusion is the strongest, with a weighted Jaccard value of 0.108, suggesting that the two lineages share more references. The coupling of AI with Physics and Statistical Fusion is weaker, with weighted Jaccard values of 0.025 and 0.031, respectively. Hybrid also exhibits coupling with Physics, Statistical Fusion, and AI, with weighted Jaccard values of 0.053, 0.048, and 0.044, respectively. This indicates that Hybrid plays a connecting role among different methodological lineages.

To further assess the robustness of these methodological evolution patterns, the sensitivity analysis examined the influence of the Other category, which comprised 516 (38.9%) of the 1328 publications under the original classification (S0). The strict (S2) and expanded (S3) scenarios conditionally reassigned 12 and 60 publications, respectively, from Other to the core methodological lineages (Table 4). Statistical Fusion remained the largest core lineage across all scenarios. The combined share of AI and Hybrid within the four core lineages increased from 4.99–5.32% during 2000–2019 to 27.31–27.52% during 2020–2025. Physics and Statistical Fusion consistently exhibited the strongest overall weighted reference coupling (WJ = 0.1077–0.1114). The principal patterns remained consistent across the tested scenarios, while category sizes, temporal characteristics, and coupling strengths showed varying degrees of sensitivity to classification rules.

Overall, radar precipitation uncertainty research is undergoing a transition in its methodological system. Statistical Fusion and Physics provide the foundation, while AI and Hybrid represent rapidly growing methodological directions in recent years. Hybrid connects physical mechanisms, statistical fusion, and data-driven methods. The methodological evolution of this field is therefore characterized by the integration of conventional correction approaches, physical mechanisms, statistical fusion, and AI methods.

Table 4. Sensitivity of methodological lineage patterns to the treatment of the Other category (2000–2025).

Indicator	S0	S1	S2	S3
Publications included (n)	1328	812	1328	1328
Physics (n)	231	231	234	258
Statistical Fusion (n)	481	481	489	510
AI (n)	44	44	45	48
Hybrid (n)	56	56	56	56
Other (n)	516	—	504	456

Table 4. *Cont*.

Indicator	S0	S1	S2	S3
Other share (%)	38.86	—	37.95	34.34
AI + Hybrid share, 2000–2019 (%)	5.23	5.23	5.32	4.99
AI + Hybrid share, 2020–2025 (%)	27.52	27.52	27.31	27.31
Strongest coupling pair	P–SF	P–SF	P–SF	P–SF
Strongest coupling (WJ)	0.1077	0.1077	0.1078	0.1114

Note: S0 denotes the original five-category classification; S1 includes only the four core lineages; and S2–S3 represent strict and expanded rule-based sensitivity scenarios with conditional reassignment from Other. The em dash (—) indicates that the Other category is excluded from scenario S1 and is therefore not applicable. AI + Hybrid shares are calculated within the four core lineages for each period. P–SF denotes Physics–Statistical Fusion, and WJ is the weighted Jaccard index of shared references. Reference weights are based on all 1328 publications and held constant across scenarios.

3.4.2. Characteristics of Bridging Publications and Knowledge Transfer

Based on the preceding methodological lineage analysis, this study further identified key publications that connect different methodological lineages. Figure 10a–c show the temporal distribution of bridging publications, changes in bridging strength across different periods, and knowledge-transfer evidence from representative bridging publications, respectively. Table 5 lists the knowledge connection targets, bridging types, and main bridging characteristics of these publications. Overall, bridging publications are mainly concentrated in AI and Hybrid studies, with Hybrid showing a more prominent bridging role. These publications link AI/Hybrid methods with existing physics-based and statistical methods mainly through error correction, multi-source merging, physical-variable modeling, and hybrid framework construction.

Table 5. Knowledge connections and bridging characteristics of representative bridging publications.

Bridging Type	Representative Publication	Main Methodological Lineage	Linkage Node	Bridging Characteristic
Hydrological-response and flood-forecasting bridge	Hydrologic Evaluation of Rainfall Estimates from Radar, Satellite, Gauge, and Combinations on Ft. Cobb Basin, Oklahoma, Journal of Hydrometeorology [62]	Hybrid	Multi-source QPE–hydrological model–runoff/flood response	Applies multi-source precipitation estimation evaluation to runoff and flood simulation, linking QPE errors with flood-forecasting applications.
Dual-polarization radar QPE algorithm and error-correction bridge	An Adaptive Rainfall Estimation Algorithm for Dual-Polarization Radar, IEEE Geoscience and Remote Sensing Letters [63]	Hybrid	Dual-polarization physical information–adaptive algorithm–QPE correction	Integrates dual-polarization radar information, logistic regression-based rainfall relationship selection, and neural-network estimation within an adaptive QPE framework, linking physical observations, statistical methods, and AI.
Environment-condition-driven QPE uncertainty modeling bridge	Uncertainty Analysis of Radar Rainfall Estimates Induced by Atmospheric Conditions Using Long Short-Term Memory Networks, Journal of Hydrology [64]	Hybrid	Atmospheric conditions–radar errors–LSTM uncertainty modeling	Characterizes the influence of environmental conditions on radar errors, linking error-source interpretation with AI-based uncertainty modeling.
Radar precipitation estimation and nowcasting bridge	Dynamic ANN for Precipitation Estimation and Forecasting from Radar Observations, Journal of Hydrology [65]	Hybrid	Radar observation–dynamic ANN–QPE/QPF	Uses radar observations for both estimation and short-term forecasting, linking QPE correction with QPF applications.

Table 5. *Cont*.

Bridging Type	Representative Publication	Main Methodological Lineage	Linkage Node	Bridging Characteristic
Radar spatial-scale, AI estimation, and hydrological-response bridge	Estimation of Optimal Grid Size for Radar Reflectivity Using a SWAT Model, Journal of Hydro-Environment Research [66]	AI	Radar grid scale–ANN estimation–SWAT hydrological response	Links radar-scale selection, AI estimation, and hydrological simulation, revealing the transmission of scale uncertainty to runoff response.
Radar–gauge fusion and real-time QPE bridge	RadarGaugeNet: Radar-Rain-Gauge-Based AI Architecture for Real-Time Quantitative Precipitation Estimation, IEEE Transactions on Geoscience and Remote Sensing [67]	AI	Radar observation–gauge constraint–real-time AI-based QPE fusion	Integrates radar and gauge information using AI, linking multi-source correction, real-time QPE, and operational applications.



Figure 10. Temporal distribution, bridging scores, and representative evidence of bridging publications: (**a**) Temporal distribution of bridging publications. (**b**) Bridging scores across different periods. (**c**) Evidence cards of representative bridging publications. Note: Publication titles in panel (**c**) are abbreviated with ellipses for display purposes. Complete titles and corresponding methodological descriptions are provided in Table 5.

Figure 10a shows that the number of bridging publications was limited during 2000–2010 and began to increase after 2010. After 2020, the number of bridging publications increased markedly, with publication counts remaining high during 2022–2025. Figure 10b further indicates that bridging scores varied across periods. Hybrid publications maintained relatively high scores in several periods, especially during 2010–2014 and 2020–2024. AI publications also showed high scores in some periods, but their distribution was more scattered. This suggests that the strength of connections between AI studies and physical mechanisms, statistical correction frameworks, and specific application problems varies across tasks.

The representative evidence cards in Figure 10c show that publications with high bridging scores are mainly concentrated in the Hybrid lineage. These publications usually address radar precipitation estimation, error correction, or multi-source merging within physical-mechanism and statistical-fusion frameworks. In the evidence cards, four Hybrid publications simultaneously connect the Hybrid, Physics, and Statistical Fusion lineages, while two AI publications simultaneously connect the AI, Physics, and Statistical Fusion lineages. These connections reveal shared bibliographic foundations across methodological lineages. Table 5 further complements the bibliographic evidence by illustrating the practical methodological linkages represented in these publications. This result indicates that Hybrid publications play a more consistent role in connecting methodological lineages, whereas AI publications mainly establish links with the traditional knowledge system through specific task contexts.

Table 5 further illustrates three forms of methodological connections through representative case studies. The first involves multi-source precipitation estimation and hydrological evaluation. Gourley et al. evaluated radar, satellite, gauge, and combined rainfall products using hydrological simulations, linking precipitation estimation uncertainty with runoff responses [62]. The second focuses on adaptive QPE and error correction. Kou et al. integrated dual-polarization radar information, statistical relationship selection, and neural-network estimation [63], while Yang et al. incorporated atmospheric conditions and radar–gauge error information into LSTM-based uncertainty modeling [64]. The third involves AI-assisted forecasting and hydrological-model coupling. Chiang et al. combined three-dimensional radar observations and precipitation-motion information with a dynamic ANN for QPE and QPF [65], while Jeong et al. linked ANN-based rainfall estimation with SWAT simulations to assess hydrological responses to radar grid-scale variations [66]. Sarafian et al. further integrated radar and gauge information into an AI-based real-time QPE framework [67]. Together, these studies demonstrate practical methodological connections among physical observations, statistical approaches, AI modeling, and hydrological applications, complementing the citation-based coupling evidence.

Overall, bridging publications reveal the main pathways through which AI/Hybrid methods have entered radar precipitation uncertainty research. After 2020, cross-lineage connections strengthened with the development of AI methods, multi-source merging, and hybrid modeling. Compared with single AI methods, Hybrid methods more consistently connect Physics, Statistical Fusion, and data-driven approaches. Representative publications further indicate that emerging modeling methods mainly establish links with the existing physics–statistics knowledge system through radar precipitation estimation, error correction, multi-source merging, physical observation constraints, and hydrological forecasting.

3.5. Alignment of Research Themes with Operational Radar–Hydrology Systems

To examine the operational relevance of research topic popularity, this study compared the 19 identified research topics with documented forecasting and warning functions across six representative radar–hydrology systems: NOAA in the United States, China MWR,

JMA in Japan, EFAS in Europe, FFC/Met Office in the United Kingdom, and BoM in Australia (Table 6). Among the 114 possible topic–system relationships, 31 direct task-level correspondences were identified based on publicly documented operational functions, involving seven research topics. In terms of system-level distribution, FFC/Met Office corresponded to seven topics, followed by NOAA, JMA, and BoM with six topics each, China MWR with four topics, and EFAS with two topics.

Table 6. Operational functions and corresponding research topics across six representative radar–hydrology systems.

Operational System	Main Operational Functions	Corresponding Topics	No. of Topics
NOAA (MRMS/NWM)	Multisensor QPE, hydrological modelling, and flood forecasting	T2, T3, T4, T5, T9, T14	6
China MWR	Precipitation monitoring, hydrological forecasting, and flood warning	T2, T3, T5, T9	4
JMA	Radar rainfall estimation, nowcasting, and flood warning	T2, T3, T4, T5, T9, T14	6
EFAS	Hydrological forecasting and flood-risk assessment	T3, T9	2
FFC/Met Office	Rainfall forecasting, surface-water flood guidance, and risk warning	T2, T3, T4, T5, T7, T9, T14	7
BoM	Precipitation monitoring, hydrological modelling, and flood forecasting	T2, T3, T4, T5, T9, T14	6

Note: All 19 research topics were evaluated. The table reports the seven topics for which direct task-level correspondences with publicly documented operational functions were identified. Topic IDs and standardized labels are provided in Appendix A Table A1.

The six operational systems reflect different priorities in precipitation monitoring, flood forecasting, and risk warning. NOAA's MRMS supports multi-radar and multisensor precipitation estimation, while its National Water Model (NWM) provides hydrological simulation and streamflow forecasting [68–70]. China's Ministry of Water Resources (MWR) promotes coordinated rainfall and streamflow monitoring using precipitation radars, rain gauges, and hydrological stations to strengthen flood forecasting and early warning [71]. The Japan Meteorological Agency (JMA) integrates radar and rain-gauge observations for precipitation analysis and nowcasting and provides flood warning services [72]. The European Flood Awareness System (EFAS) integrates hydrological forecasts with flood-impact and risk assessment [73,74]. The UK Flood Forecasting Centre (FFC)/Met Office focuses on flood-risk guidance and emergency decision support [75,76]. Australia's Bureau of Meteorology (BoM) combines meteorological and hydrological observations with forecasting models to support hydrological prediction and flood warnings [77]. These documented operational functions provide a practical basis for examining the correspondence between research topic popularity and forecasting, warning, and decision-support requirements.

In terms of topic correspondence, hydrologic streamflow modelling (T3) and rainfall–flood coupling (T9) were associated with all six systems. Dual-polarimetric radar rainfall estimation (T2) and radar precipitation estimation (T5) corresponded to five systems, while radar–gauge rainfall comparison and correction (T4) and geostatistical radar–gauge merging (T14) corresponded to four systems. Urban flood and sewer response (T7) showed a direct correspondence only with FFC/Met Office. For the remaining 12 topics, the available operational descriptions provided insufficient evidence to establish direct task-level correspondence.

Regarding research popularity, T2 had the largest publication count among the seven corresponding topics, with 118 publications (8.9%), followed by T3 with 96 (7.2%), T4 with 94 (7.1%), and T5 with 84 (6.3%). T7, T9, and T14 accounted for 71 (5.3%), 65 (4.9%), and 41 (3.1%) publications, respectively. Overall, radar precipitation estimation and correc-

tion attracted substantial research attention, while hydrologic streamflow modelling (T3) and rainfall–flood coupling (T9) showed the broadest functional correspondence across operational systems. This pattern indicates that publication popularity and operational functional coverage vary across research topics.

4. Discussion

4.1. Topic Evolution and Emerging Hotspots

Figure 11 shows the evolutionary trajectories of the relative shares of different topics across periods. Overall, radar precipitation uncertainty research is characterized by the co-development of a stable knowledge core and emerging application-oriented directions [29,78]. Early studies mainly focused on radar observation errors, the complementary relationship between radar and rain gauges, and multi-source data merging mechanisms. These studies provided a conceptual and methodological foundation for subsequent QPE correction, error propagation analysis, and hydrological applications [10,54,79]. With the development of radar network products, dual-polarization observations, and multi-radar multi-sensor products, QPE correction has gradually become an important basis for providing reliable inputs to hydrological simulation, flood forecasting, and risk assessment [4,53].

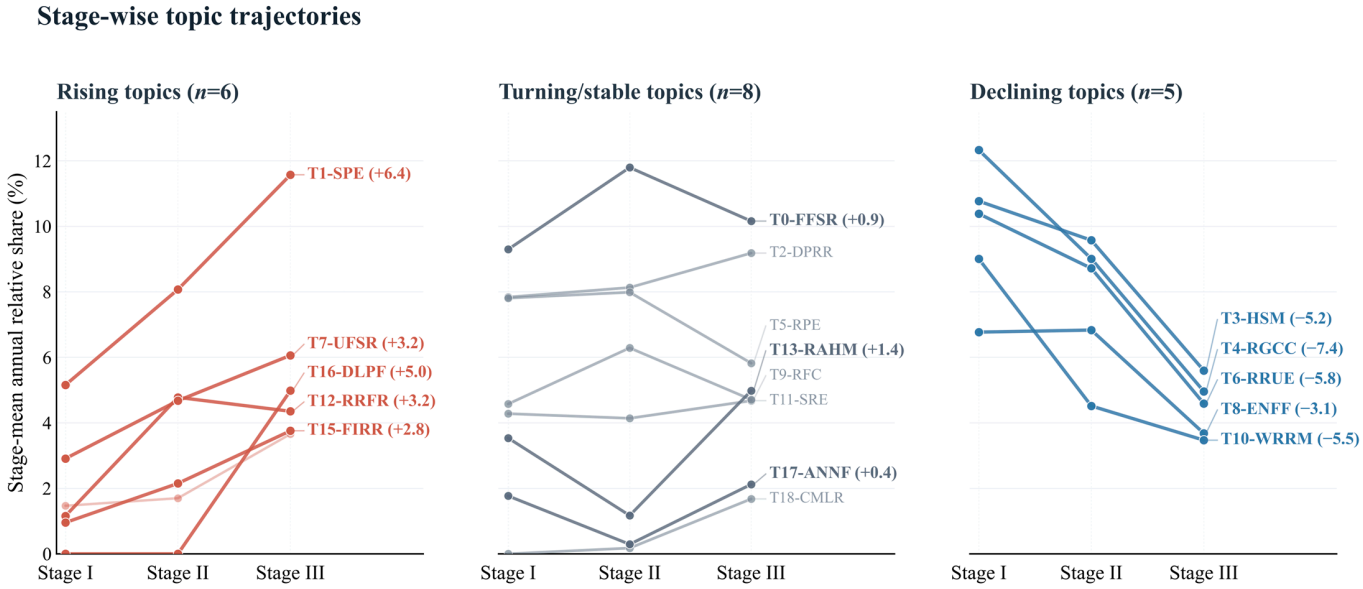


Figure 11. Topic evolution trajectories and emerging hotspots. Note: Full topic names are provided in Appendix A Table A1.

Topic expansion has been mainly driven by changes in application scenarios [80,81]. Extreme rainfall, flooding, urban pluvial flooding, and real-time warning have increased the need for hydrologically meaningful interpretations of precipitation products. Research attention has therefore extended from the statistical accuracy of products to the impacts of precipitation errors on runoff processes, flood-peak timing, inundation extent, and warning decisions [82,83]. Studies on urban hydrology and watershed simulation show that precipitation spatiotemporal variability, observation resolution, and data merging strategies can alter hydrological response results. As a result, error propagation, ensemble forecasting, probabilistic uncertainty representation, and operational usability have gradually become recent hotspots [32,84].

From the perspective of topic maturity, radar precipitation estimation, radar–gauge correction, multi-source merging, and dual-polarization QPE have formed relatively clear technical pathways [19,85,86]. The continuing value of these mature topics lies mainly in two

aspects. First, they provide an interpretable basis for studying error structures. Second, they provide sustained evidence for hydrological response diagnosis and risk assessment [19,85]. By contrast, AI-assisted QPE, Hybrid modeling, probabilistic nowcasting, and flood-risk expression represent new growth directions. These directions point to a more specific question: how to improve the usability of precipitation estimation in dynamic hydrological forecasting and emergency decision-making [3,9].

Overall, the mature core of the field remains concentrated in error identification, data correction, and multi-source merging, whereas emerging directions are more closely related to hydrological response, scale effects, and risk judgment. Future research should further clarify which errors affect hydrological response, which scale effects change risk judgment, and which new methods can support warning and reservoir-operation decisions [29,78].

4.2. From Error Correction to Hydrological Uncertainty Propagation

Previous studies have highlighted hydrological uncertainty propagation as an important research issue in radar precipitation applications [87,88]. Once QPE errors enter a hydrological system, they continue to propagate through runoff generation, flow concentration, and channel routing. Their effects are eventually expressed as uncertainty in runoff processes, flood-peak characteristics, and inundation results [14,43,52]. Error correlation structure, precipitation spatiotemporal scale, basin area, soil moisture, land-surface conditions, and model parameters can all modify the influence of radar precipitation errors on hydrological processes [15,27].

Existing studies have revealed both amplification and attenuation mechanisms in error propagation [89]. In small basins, urban catchments, and short-duration convective storms, errors in rainfall-core location, peak intensity, and timing can translate into errors in flood-peak magnitude and timing, thereby affecting warning lead time and reservoir-operation windows [44,82,90]. In larger basins, spatial averaging, channel storage, and flow-routing smoothing can attenuate local QPE errors. Positional errors in extreme precipitation grids may also lead to underestimation of local risks [6,16]. For deep-convective precipitation, evidence from studies of convective and extreme rainfall highlights the importance of rainfall intensity, precipitation location and timing, and radar observation quality in shaping QPE uncertainty and its hydrological impacts [91–93]. Overall, the propagation of QPE errors into hydrological processes is jointly influenced by rainfall characteristics, basin scale, antecedent wetness, and model structure [23,92]. Future research should develop probabilistic QPE ensembles for deep convection and extreme rainfall, focusing on spatiotemporal error correlation and its effects on flood peaks, peak timing, and warning reliability.

Future research should further strengthen the decomposition of multiple sources of uncertainty. In addition to QPE errors, QPF forecast errors, model parameters, initial states, boundary conditions, terrain-data accuracy, and hydrodynamic roughness can also affect flood-risk outputs [94,95]. Comparing deterministic simulations driven by different precipitation products alone is insufficient for identifying the relative contributions of precipitation-input errors, model-structure errors, and validation-data errors [96]. Subsequent studies could combine ensemble simulation, global sensitivity analysis, and error-propagation diagnostics to quantify how different error sources contribute under different basin conditions, storm types, and model structures. More importantly, research should identify which precipitation errors affect flood peak, peak timing, and inundation extent, and to what extent they further change warning thresholds and risk judgments [46,97].

Evaluation frameworks should also increasingly account for hydrological responses and risk outcomes [96]. Bias, RMSE, correlation coefficient, and hit rate remain useful for characterizing the statistical accuracy of QPE products, but these metrics cannot fully explain uncertainty in hydrological and flood-risk outcomes [39,98]. For warning and

risk-management applications, evaluation metrics should further cover flood-peak error, peak-timing error, inundation-extent bias, exceedance probability, warning hit rate, and the probability of risk underestimation [81,99,100]. With the rapid development of real-time flood nowcasting and digital-twin flood frameworks, precipitation ensembles, real-time updating, and risk-indicator outputs are becoming important pathways that connect error correction with operational applications [8,9]. A key future task is to place QPE, hydrological response, and risk-oriented evaluation within the same analytical chain, so that error-correction results can directly support probabilistic forecasting, threshold triggering, and risk-informed decision-making.

4.3. Integration of Methodological Lineages and Future Research Directions

Previous studies have provided a foundation for integrating physical mechanisms, statistical fusion, and AI methods [21,101,102]. Physics-based methods can explain radar-variable relationships, microphysical processes, and error sources. Statistical fusion methods can exploit complementary information from radar, rain gauges, satellites, and reanalysis data. AI methods can extract nonlinear features from large-scale spatiotemporal data [10,54,101]. For radar QPE, rainfall estimation relationships based on ZDR and KDP provide physically interpretable estimates and a basis for error analysis [19,103]. AI methods can complement these relationships by modeling nonlinear radar–rainfall relationships and characterizing QPE uncertainty under varying atmospheric conditions [60,64]. These methods correspond to different sources of uncertainty and have different application contexts. Future research should promote their coordinated use within the same hydrological risk chain, rather than focusing only on the accuracy optimization of individual precipitation products.

In recent years, AI and Hybrid methods have provided new tools for radar precipitation estimation, polarimetric radar QPE, and precipitation nowcasting [3,19,60,104]. Hybrid physics–AI, physics-constrained deep learning, and differentiable modeling emphasize the embedding of process priors, conservation relationships, and model-structure knowledge into data-driven frameworks. These approaches can help improve physical consistency, interpretability, and extrapolation capability under extreme precipitation, complex terrain, and data-sparse conditions [26,30]. The representative bridging publications reveal diverse forms of methodological complementarity, including physics-informed learning, statistical selection, multi-source observational supervision, and sequential coupling with hydrological models. These cross-method connections highlight a promising research direction that brings together physical understanding, statistical information, and data-driven modeling to support future advances in radar precipitation estimation and hydrological forecasting. Future studies could further explore how radar observation mechanisms, error structures, topographic effects, and hydrological-response factors can be embedded into AI models.

The next priority for methodological integration is to develop uncertainty products, especially probabilistic forecast products, that are calibratable, interpretable, and usable for risk decision-making [22,105,106]. Radar precipitation uncertainty includes both explainable observational error mechanisms and epistemic uncertainty caused by model structure, sample scarcity, and extrapolation to extreme events [107]. Therefore, AI and Hybrid models should not only output deterministic precipitation fields. A more useful direction is to provide precipitation estimates, error structures, and uncertainty ranges together and evaluate them in terms of reliability, calibration, spatial consistency, and hydrological benefits [21,22]. Future research should also pay more attention to probabilistic forecasting across lead times, especially the uncertainty linkage among radar extrapolation, NWP ensembles, and hydrological models.

Operational implementation remains an important challenge [108]. Radar precipitation uncertainty research has begun to support flash-flood warning, urban pluvial flood forecasting, reservoir operation, and risk management. However, the pathway linking probabilistic precipitation estimates, model outputs, and decision indicators requires further development [46,83]. Future research can be organized around problem-oriented fusion modeling: characterizing multi-source precipitation heterogeneity at the observation end, generating calibratable probabilistic precipitation ensembles at the forecasting end, identifying error amplification and attenuation pathways at the hydrological and hydrodynamic end, and producing exceedance probabilities, inundation risks, and warning-trigger indicators at the application end [109,110]. Digital twin basins can serve as closed-loop platforms for validation and operational implementation in this process. Their practical value should be demonstrated through real-time data updates, model feedback correction, and verification of decision indicators [9,28].

4.4. Weather Radar QPE Methods and Uncertainty Characteristics

Dual-polarimetric radar rainfall estimation provides important opportunities for reducing QPE errors by incorporating observational information related to precipitation microphysics [53]. Previous studies have shown that, compared with conventional single-variable Z–R relationships, rainfall estimation methods integrating polarimetric variables such as reflectivity (Z), differential reflectivity (ZDR), and specific differential phase (KDP) can better characterize precipitation microphysical properties and improve QPE accuracy [18,103]. Recent approaches combining adaptive selection of polarimetric variables, adjustment of rainfall estimation relationships, and deep learning have further enhanced the representation of complex nonlinear relationships in precipitation estimation, providing additional opportunities for reducing QPE errors [19,63]. However, the performance of different methods remains dependent on precipitation characteristics and radar observation quality [19]. KDP is relatively insensitive to reflectivity calibration errors and precipitation attenuation, offering advantages under heavy rainfall conditions, whereas phase noise may affect its estimation accuracy during light rainfall [53,103]. ZDR provides information related to raindrop size distributions, but its retrieval accuracy depends on calibration and attenuation correction [53]. Overall, the relative advantages of different QPE methods are strongly dependent on application conditions. Adaptive estimation incorporating precipitation type, radar observation quality, and multiple polarimetric variables, together with reliability assessment across different regions and precipitation conditions, represents an important direction for improving QPE accuracy and uncertainty characterization.

Radar–gauge correction and multi-source statistical merging provide complementary approaches to improving QPE accuracy. Mean-field bias correction, local bias correction, and geostatistical merging can reduce systematic and local errors by incorporating ground-based observational constraints [111]. Operational systems such as MRMS integrate radar, rain gauges, and other observational data to generate QPE products [4]. The performance of these methods depends on gauge density, observation quality, spatial representativeness, and the error structure of background precipitation fields [27,68]. In complex terrain and sparse gauge networks, radar beam blockage and vertical precipitation variability further affect correction accuracy [68]. AI and Hybrid methods may provide additional improvements through nonlinear error correction and multi-source information integration, although their performance under different precipitation conditions requires further validation [19,60].

Overall, the uncertainty characteristics of radar QPE methods indicate that their relative performance depends on precipitation type, observation conditions, and correction strategies [27,68,103]. Future evaluations should compare different QPE approaches using

consistent datasets, temporal scales, and performance metrics, including bias, RMSE, spatial error characteristics, and probabilistic reliability [15,27]. Particular attention should be given to heavy rainfall, complex terrain, and sparse observation networks, where error sources and observational constraints can differ substantially [68]. Such comparisons would help identify suitable QPE methods for different application conditions and provide a more reliable basis for hydrological forecasting.

4.5. Limitations

This study has several limitations. The review corpus was derived from the Web of Science Core Collection. Although this database provides broad coverage of hydrology, remote sensing, and atmospheric sciences, relevant studies indexed only in other databases may not have been included. In addition, the reviewed literature covers diverse radar systems, precipitation products, hydrological settings, spatial and temporal scales, and definitions of uncertainty. Such heterogeneity limits direct comparison among individual studies and should be considered when interpreting the overall topic structure and methodological trends identified in this review. Accordingly, aggregated bibliometric statistics, including publication counts, topic proportions, and methodological-lineage distributions, were interpreted as indicators of research activity and knowledge structure rather than standardized measures of model performance.

The analyses were primarily based on bibliographic metadata, titles, abstracts, keywords, and citation information rather than systematic extraction of full-text quantitative results. The use of automated semantic screening, Transformer-based representations, BERTopic modeling, and methodological classification also involves choices related to similarity thresholds, model parameters, and topic interpretation. Although robustness tests and manual validation were used to improve the reliability of the analytical framework, some uncertainty in topic boundaries and methodological classifications remains unavoidable. Future reviews could incorporate multiple bibliographic databases, richer full-text information, and updated literature to further examine the stability and generalizability of the identified research structure. Publication-year temporal centroids characterize the temporal distribution of research activity.

In the original classification, 516 publications (38.9%) were assigned to Other. The S0–S3 sensitivity analysis showed that the predominance of Statistical Fusion, the recent development of AI and Hybrid, and the strongest reference coupling between Physics and Statistical Fusion remained consistent across scenarios, indicating that the high proportion of Other had a limited influence on the principal conclusions regarding methodological evolution. Variations in classification rules primarily affected category sizes, temporal statistics, and coupling strengths. Future reviews could incorporate multiple bibliographic databases, richer full-text information, multilabel classification, and updated literature to further examine the stability and generalizability of the identified research structure and cross-lineage interactions.

5. Conclusions

Based on Transformer-based semantic representation and BERTopic topic modeling, this study systematically analyzed the topic structure, evolutionary patterns, and methodological lineages of radar precipitation uncertainty research from 2000 to 2025. The main conclusions are as follows.

(1) Radar precipitation uncertainty research entered a phase of rapid development after 2009 and maintained a high publication level after 2013. Related studies are mainly distributed across hydrology, hydrometeorology, remote sensing, and atmospheric sciences. The international collaboration network is centered on the USA, with China

and the UK making substantial contributions and several European countries showing active participation.

(2) Semantic topic modeling identified 19 micro-level topics, which were further grouped into four high-level research categories: measurement error identification and correction, uncertainty characterization and modeling, error propagation and scale effects, and operational applications and risk decision-making. Current research remains concentrated on observational error identification, data correction, and hydrological impact analysis. Topics related to explicit uncertainty modeling, probabilistic risk expression, and operational implementation remain relatively underdeveloped.

(3) The topic semantic proximity relationships and higher-order clustering results show that the field is mainly organized around four higher-order branches: observation and correction, uncertainty and scale effects, hydrological propagation, and AI-driven forecasting. Overall, radar precipitation uncertainty research has gradually moved beyond the accuracy evaluation of individual products and has begun to focus on the links among observational errors, hydrological propagation, intelligent forecasting, and risk decision-making.

(4) Methodological lineage analysis shows that Statistical Fusion is the dominant methodological lineage, while Physics provides an important foundation. AI and Hybrid methods have grown markedly in recent years. Physics and Statistical Fusion show strong knowledge coupling, whereas the coupling between AI and traditional methods remains relatively limited. Hybrid methods play a bridging role among Physics, Statistical Fusion, and AI, indicating that methodological evolution in this field is mainly characterized by the coordinated use and complementary integration of multiple methods.

(5) Bridging publications indicate that AI and Hybrid methods are being embedded into the existing knowledge system through error correction, multi-source precipitation merging, radar-variable modeling, physical observation constraints, and AI-based nowcasting. Future research should further integrate explainable AI, physical constraints, probabilistic modeling, and hydrological-response consistency testing. This will help shift the field from product-level accuracy optimization toward chain-wide representation that connects observation, forecasting, hydrological propagation, and risk decision-making.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/rs18213762/s1, Figure S1: PRISMA 2020 flow diagram of literature identification, screening, eligibility, and inclusion, prepared using the PRISMA 2020 reporting framework [31] and the PRISMA2020 Shiny application [112]; Table S1: Full list of studies included in the review corpus (n = 1328); Table S2: Eligibility criteria and literature search strategy.

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Data Availability Statement: No new original data were generated in this study. The bibliographic data analyzed were obtained from the Web of Science Core Collection and are subject to its licensing terms. The full list of included studies is provided in Supplementary Table S1, and all derived results

are presented in the article and Appendix A. The analytic code and additional processed materials supporting the analyses are available from the corresponding author upon reasonable request.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
ANN	Artificial Neural Network
CML	Commercial Microwave Link
c-TF-IDF	class-based Term Frequency–Inverse Document Frequency
DOI	Digital Object Identifier
HDBSCAN	Hierarchical Density-Based Spatial Clustering of Applications with Noise
LSTM	Long Short-Term Memory
MCP	Multi-Country Publications
NWP	Numerical Weather Prediction
QPE	Quantitative Precipitation Estimation
QPF	Quantitative Precipitation Forecasting
RMSE	Root Mean Square Error
SWAT	Soil and Water Assessment Tool
UMAP	Uniform Manifold Approximation and Projection

Appendix A

Table A1. Correspondence among topic IDs, original keyword strings, standardized topic labels, and abbreviations.

Topic ID	Original Keyword String	Standardized Topic Label	Abbreviation
T0	Flash/Flood/Spatiotemporal/Response	Flash-flood spatiotemporal response	FFSR
T1	Satellite/Precipitation/Estimation	Satellite precipitation estimation	SPE
T2	Dual/Polarimetric/Radar/Bands	Dual-polarimetric radar rainfall estimation	DPRR
T3	Streamflow/Hydrologic	Hydrologic streamflow modelling	HSM
T4	Radar/Gauge/Rain/Rainfall	Radar-gauge rainfall comparison and correction	RGCC
T5	Precipitation/Radar/Rainfall	Radar precipitation estimation	RPE
T6	Uncertainty/Rainfall/Radar/Errors	Radar rainfall uncertainty and errors	RRUE
T7	Urban/Flood/And/Sewer/Response	Urban flood and sewer response	UFSR
T8	Forecasts/Nowcasting/Ensemble/Flood	Ensemble nowcasting and flood forecasting	ENFF
T9	Rainfall/Flood/Radar	Rainfall-flood coupling	RFC
T10	Radar/Weather/Rainfall	Weather-radar rainfall modelling	WRRM
T11	Rainfall/Spatial/Resolution	Spatial-resolution effects in rainfall estimation	SRE
T12	Radar/Rainfall/Flood	Radar rainfall and flood response	RRFR
T13	Assimilation/Dsd/Raindrop/Precipitation	Rainfall assimilation and hydrologic modelling	RAHM
T14	Merging/Gauge/Radar/Rain	Geostatistical radar-gauge merging	GRGM
T15	Flood/Inundation/Rainfall	Flood inundation and rainfall response	FIRR
T16	Learning/Deep/Precipitation	Deep-learning precipitation forecasting	DLPF
T17	Ann/Radar/Forecasting	ANN-based radar rainfall forecasting	ANNF
T18	Cml/Link/Microwave/Commercial	CML-based rainfall retrieval	CMLR

Table A2. Temporal centroids and representative publications of topics.

Topic ID	Standardized Topic Label	Mean Temporal Centroid Year (MTC Year)	Representative Publications
0	Flash-flood spatiotemporal response	2014.72	When does higher spatial resolution rainfall information improve streamflow simulation? An evaluation using 3620 flood events, Hydrol. Earth Syst. Sci. [113]
1	Satellite precipitation estimation	2016.57	Assessment of GPM IMERG and radar quantitative precipitation estimation (QPE) products using dense rain gauge observations in the Guangdong-Hong Kong-Macao Greater Bay Area, China, Atmos. Res. [114]

Table A2. *Cont*.

Topic ID	Standardized Topic Label	Mean Temporal Centroid Year (MTC Year)	Representative Publications
2	Dual-polarimetric radar rainfall estimation	2014.84	Estimation of Light Rainfall Using Ku-Band Dual-Polarization Radar, IEEE Trans. Geosci. Remote Sens. [115]
3	Hydrologic streamflow modelling	2013.09	Assimilation of streamflow and in situ soil moisture data into operational distributed hydrologic models: Effects of uncertainties in the data and initial model soil moisture states, Adv. Water Resour. [116]
4	Radar-gauge rainfall comparison and correction	2011.64	Evaluation of the value of radar QPE data and rain gauge data for hydrological modeling, Water Resour. Res. [117]
5	Radar precipitation estimation	2014.04	Probabilistic precipitation rate estimates with ground-based radar networks, Water Resour. Res. [118]
6	Radar rainfall uncertainty and errors	2012.01	Impact of Gauge Representative Error on a Radar Rainfall Uncertainty Model, J. Appl. Meteorol. Climatol. [119]
7	Urban flood and sewer response	2015.58	The complexities of urban flood response: Flood frequency analyses for the Charlotte metropolitan region, Water Resour. Res. [120]
8	Ensemble nowcasting and flood forecasting	2013.14	Understanding uncertainty in distributed flash flood forecasting for semiarid regions, Water Resour. Res. [121]
9	Rainfall-flood coupling	2014.71	Assessment on the function of reservoirs for flood control during typhoon seasons based on a distributed hydrological model, Hydrol. Process. [122]
10	Weather-radar rainfall modelling	2011.76	Technical Note: An open source library for processing weather radar data (wradlib), Hydrol. Earth Syst. Sci. [123]
11	Spatial-resolution effects in rainfall estimation	2015.02	Impact of spatial and temporal resolution of rainfall inputs on urban hydrodynamic modelling outputs: A multi-catchment investigation, J. Hydrol. [90]
12	Radar rainfall and flood response	2015.77	Correcting the radar rainfall forcing of a hydrological model with data assimilation: application to flood forecasting in the Lez catchment in Southern France, Hydrol. Earth Syst. Sci. [124]
13	Rainfall assimilation and hydrologic modelling	2017.4	A study on WRF radar data assimilation for hydrological rainfall prediction, Hydrol. Earth Syst. Sci. [125]
14	Geostatistical radar-gauge merging	2016.63	A Review of Radar-Rain Gauge Data Merging Methods and Their Potential for Urban Hydrological Applications, Water Resour. Res. [54]
15	Flood inundation and rainfall response	2017.08	Urban flood risk warning under rapid urbanization, Environ. Res. [126]
16	Deep-learning precipitation forecasting	2023.38	Utilizing deep learning for near real-time rainfall forecasting based on radar data, Phys. Chem. Earth. [127]
17	ANN-based radar rainfall forecasting	2016.52	A nonlinear spatio-temporal lumping of radar rainfall for modeling multi-step-ahead inflow forecasts by data-driven techniques, J. Hydrol. [128]
18	CML-based rainfall retrieval	2019.69	Commercial microwave links for urban drainage modelling: The effect of link characteristics and their position on runoff simulations, J. Environ. Manage. [129]

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