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A systematic review of methods for identifying drought-flood abrupt alternation: advances and future directions

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Drought-flood abrupt alternation (DFAA) events, characterized by compound extremes and rapid transitions, pose significant challenges for accurate identification. Although existing research has reviewed DFAA event identification, it pays insufficient attention to emerging concepts related to DFAA and characterization variables and lacks a comprehensive summary of methodological advancements under climate change. To fill these gaps, this study systematically reviews 55 publications by proposing a unified definition framework, synthesizing identification and characterization methods, evaluating recent methodological advances, and outlining future directions for improving DFAA identification. This review shows that (1) 58% of studies utilize traditional drought-flood indices and indicators, whereas 42% propose DFAA-specific indices; (2) traditional methods often disregard key DFAA characteristics, treating droughts and floods as separate events rather than as a unified process; (3) advanced methods incorporate key features such as alternation points, transition time, and transition speed, yet challenges remain in accurately capturing abrupt transitions; (4) future research should integrate multi-source datasets and apply dynamic time windows to improve DFAA identification, while aligning advances with policy to strengthen early warning and risk management.

KEYWORDS

DFAA identification methods, characterization variables, abrupt transitions, potential improvements, climate change

1 Introduction

It is indisputable that dual impacts of climate change and human activities have led to a surge in greenhouse gas emissions since the Industrial Revolution, contributing to an increase in the global average temperature, a trend expected to continue ([Intergovernmental Panel on Climate Change, 2022](#)). Consequently, the temperature increase has intensified the global hydrological cycle, resulting in more extreme events, such as droughts, floods, and wildfires, which pose serious threats to human society and ecosystems ([Hirabayashi et al., 2013](#); [Mitchell et al., 2016](#); [Wang et al., 2022](#); [Arunrat et al., 2022](#)). Among these, droughts and floods, both worldwide natural calamities, are expected to become more frequent, prolonged, and intense because of warmer air and greater variability precipitation, partially attributed to anthropogenic forcing ([Li et al., 2023](#); [Madakumbura et al., 2021](#)). Drought,

characterized by prolonged water deficits (Hao and Singh, 2015), and flooding, marked by rapid water accumulation (Wilby and Keenan, 2012), are opposing extremes of the hydrological cycle that can rapidly occur consecutively at the same location, causing a compound event referred to as drought-flood abrupt alternation (DFAA) in the context of climate change (Wu et al., 2006; Rong et al., 2020; Gao et al., 2023).

There is growing evidence that DFAA events are becoming more frequent and severe due to ongoing climate change, increasing the number of people affected, particularly in densely populated and poverty-prone regions (Winsemius et al., 2018; Zhang B. et al., 2023; Yang et al., 2013; Wu et al., 2023; Ansari and Grossi, 2022; Weng et al., 2024). Furthermore, DFAA events cause socio-economic impacts that far exceed those of individual droughts or floods, as observed in many countries, such as China (Li and Ye, 2015), India (Gond et al., 2025), and the United States (Maxwell et al., 2017). A striking example of significant loss is the economic losses from the 2011 DFAA events along the Mississippi River, which totaled an estimated \$40 billion (Ford et al., 2021). DFAA, a complex disaster with adverse impacts on ecosystems, agriculture, and socioeconomics, has sparked widespread attention from the scientific community (Liu et al., 2018; Bi et al., 2020; Dodd et al., 2023). However, the lack of a universal definition makes it difficult to identify DFAA events and their key spatiotemporal characteristics. Addressing this gap is therefore crucial for deepening the understanding of their complex nature and enhancing disaster risk reduction measures, particularly under global climate change, through insights into their spatiotemporal interactions.

In this context, the study of DFAA includes aspects such as quantitative identification, spatiotemporal distribution, dynamic processes, and driving factors. To achieve accurate identification, different indicators and indices are commonly employed, which are crucial for capturing various aspects of the DFAA conditions. Many DFAA identification methods directly adopt or extend traditional drought indices, such as the Standardized Precipitation Index (SPI, McKee et al., 1993), Standardized Precipitation Evapotranspiration Index (SPEI, Vicente-Serrano et al., 2010), and self-calibrating Palmer Drought Severity Index (SC-PDSI, Nathan et al., 2004), which quantify drought frequency and intensity. Recent reviews have highlighted their growing importance in capturing DFAA events under climate change (Xiong and Yang, 2025). Current research methods on DFAA events can be broadly categorized into the use of drought-flood indicators and indices and the construction of new DFAA indices to identify DFAA phenomena. Researchers have devoted much effort to developing different DFAA indices, such as the long-cycle DFAA index (LDFAI) (Wu, 2006), short-cycle DFAA index (SDFAI) (Shan et al., 2018), and multi-factor standardized DFAA index (MSDFI) (Bai et al., 2024). Meanwhile, most studies have focused on the characterization of DFAA events in terms of frequency, duration, and intensity, but research on other aspects, like severity and transition speed, remains scarce. Currently, research on the dynamic processes of DFAA events mainly depends on hydrological models, but studies in this area are still limited despite the importance of these processes (Visser-Quinn et al., 2019; Yang et al., 2019).

The IPCC (2012) Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation (SREX) recognizes various types of compound extreme events; however, the definition of DFAA events has not been discussed. To better characterize DFAA events, this study

concludes a unified framework that builds upon and extends the definition proposed by Bai et al. (2023). Although Bai et al. (2023) reviewed methods for identifying DFAA, they paid limited attention to emerging concepts closely related to DFAA, such as compound weather whiplash, precipitation whiplash, and lagged compound drought-flood events, which are essential for establishing a more comprehensive definition framework. Furthermore, their review emphasized index-based identification methods without systematically addressing characterization variables (i.e., directly quantifiable features of DFAA events), which are necessary for improving the accuracy of DFAA identification. In addition, a comprehensive summary of state-of-the-art identification methods for DFAA remains scarce in the literature. This systematic review consolidates the existing research on DFAA events, focusing on (a) summarizing the definitions of DFAA events and providing a conceptual foundation for their identification, (b) comprehensively reviewing approaches for identifying and characterizing DFAA events, (c) evaluating the strengths and limitations of advanced methods and revealing the region-dependent influences of major climatic drivers on DFAA events, and (d) outlining potential improvements for identifying regional DFAA in the context of climate change. By addressing these gaps, this review aims to synthesize advances in methods for identifying DFAA events and propose future directions, which can ultimately contribute to more effective disaster mitigation strategies.

2 Definitions of the DFAA event

The IPCC (2012) SREX was the first to systematically summarize and introduce the definition, types, and other aspects of compound events, describing one category as the simultaneous or successive occurrence of two or more extreme events (Leonard et al., 2014), such as concurrent precipitation and wind extremes (Martius et al., 2016; De Luca et al., 2020a), compound precipitation-temperature extremes (Wazneh et al., 2020; Dash et al., 2023), and compound drought-flood events (Fish et al., 2022). Compound events are further defined as combinations of drivers or hazards that together lead to significant impacts and are divided into temporally and spatially compounding events (Zscheischler et al., 2018; Zscheischler et al., 2020). Following this framework, Visser-Quinn et al. (2019) classified compound drought-flood events into four types: compound drought-flood, spatially compound drought-flood, temporally compound drought-flood, and spatiotemporally compound drought-flood events. Spatially compound drought-flood events refer to situations in which droughts and floods occur in different sub-basins or neighboring basins (Chen et al., 2023a), whereas temporally compound drought-flood events refer to the consecutive occurrence of droughts and floods at the same location (Chen et al., 2023b).

As shown in Figure 1, temporally compound drought-flood events can be categorized into four types: consecutive drought-flood events, successive drought-flood events, concurrent drought-flood events, and DFAA events (Marston and Ellis, 2018; He and Sheffield, 2020). It is evident that the terminologies of DFAA, dry-wet abrupt alternation, compound weather whiplash, and lagged compound drought-flood events describe similar phenomena, all with the features of abrupt transition, bidirectionality, and the same region from Table 1. In contrast, concurrent drought-flood

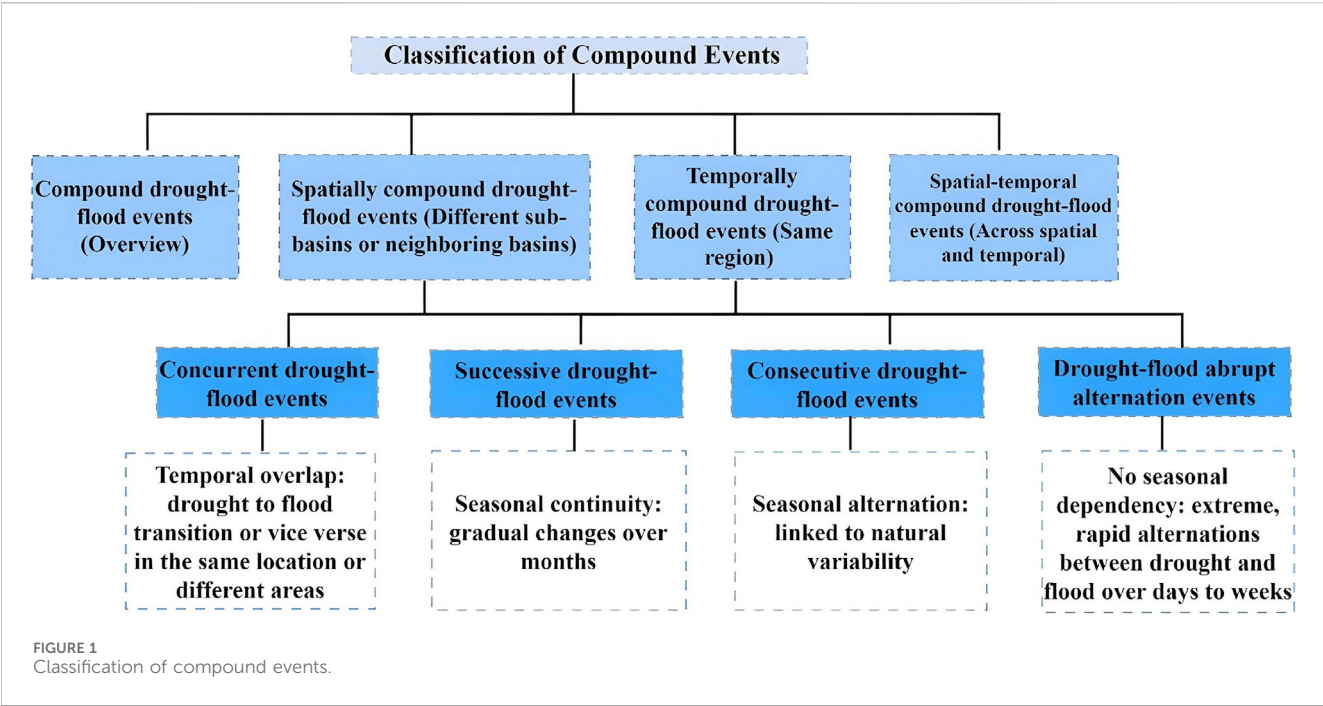
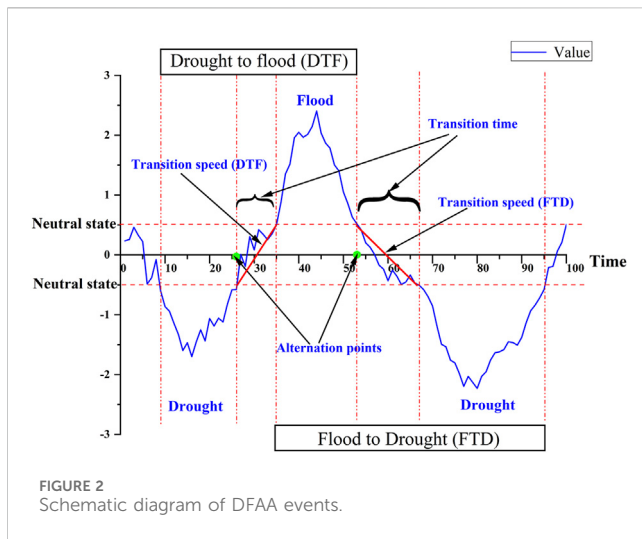


TABLE 1 Comparative summary of terminologies related to compound drought-flood events.

Terminology	Definition	Transition nature	Transition direction	Spatial consistency	Representative reference
Drought-flood abrupt alternation	Drought-flood abrupt alternation is characterized by rapid alternation between drought and flood within a short period	Abrupt transition	Bidirectional	Same region	Wu, 2006; Bi et al. (2023), Wang L. et al. (2024)
Dry-wet abrupt alternation	Dry-wet abrupt alternation refers to the alternation of dry and wet extremes over a short period, marked by rapid transition	Abrupt transition	Bidirectional	Same region	Shan L. et al. (2018), Gao et al. (2022), Liu T. et al. (2024)
Compound weather whiplash	Compound weather whiplash refers to an intraseasonal extreme event characterized by sudden shifts from prolonged drought to intense rainfall or flooding within a short period	Abrupt transition	Bidirectional	Same region	Fang and Lu (2023), Zhang Y. et al. (2023), Rahimimovaghar et al. (2024)
Lagged compound drought-flood	Lagged compound drought-flood refers to the intersection of drought and flood events over a short period, constituting an abrupt shift between two extremes	Abrupt transition	Bidirectional	Same region	He and Sheffield (2020), Rezvani et al. (2023), Deng et al. (2024)
Concurrent drought-flood	Concurrent drought-flood is defined as the simultaneous occurrence of drought and flood events across different regions or overlapping in time within the same region, representing the spatial and temporal co-occurrence of opposite hydrological extremes	No sequential transition	No direction	Multi-region or same region	De Luca et al. (2020b); Bennett et al. (2021), Chen et al. (2023a)
Successive drought-flood	Successive drought-flood is defined as successive drought followed by flood, characterized by seasonal continuity and gradual changes over several months	Gradual transition	Unidirectional	Same region	Marston and Ellis (2018), Liu et al. (2022), He et al. (2024)
Consecutive drought-flood	Consecutive drought-flood is a form of temporally compounding extreme, occurring in close temporal succession and linked to natural climate variability	Gradual transition	Bidirectional	Same region	Rashid and Wahl (2022), Brunner (2023), Matanó et al. (2024), Swain et al. (2024)



events do not involve sequential or directional transitions and lack spatial consistency. Successive and consecutive drought-flood events both emphasize gradual transitions in the same region, whereas successive events are a one-way transition from drought to flood without reversal. Successive and consecutive drought-flood events reflect gradual transitions over several weeks or months, typically caused by seasonal or natural variability (Brunner, 2023; Matanó et al., 2024), whereas DFAA events are characterized by abrupt transitions between drought and flood states within days to weeks. DFAA events are often triggered by short-term atmospheric circulation anomalies (Madrigal et al., 2024; Wang H. et al., 2024; Yu et al., 2024).

Thus, from a temporal perspective, DFAA events are compound extreme events characterized by rapid transitions between drought and flood conditions within a short period in the same area, including both drought-to-flood (DTF) and flood-to-drought (FTD) abrupt transitions (Zhao et al., 2022). Although a unified definition of DFAA events is still lacking, existing studies (Wu et al., 2006; Bai et al., 2023) provide a generalized framework for characterizing these events based on four key aspects (Figure 2): 1) the transition direction, referring to the direction of the transition between drought and flood, such as DTF or FTD; 2) the transition time, indicating the duration of the interval between drought and flood, typically spanning a few days to weeks, highlighting the abruptness of the change; 3) the alternation point, referring to the critical moment of transition between drought and flood, when climate or hydrological indicators reach a threshold, marking the beginning point when drought shifts to flood or *vice versa*; and 4) the geographical consistency, as these events usually occur within the same region or watershed, directly impacting the same system, such as agriculture or water resources.

3 Methodology of the systematic review

The literature reviewed in this study was sourced from SCOPUS and Web of Science (WoS) because of their extensive interdisciplinary coverage and reputation for high-quality

research output. The review process followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Page et al., 2021), systematically identifying, screening, and selecting relevant studies on DFAA identification methods, as shown in Figure 3.

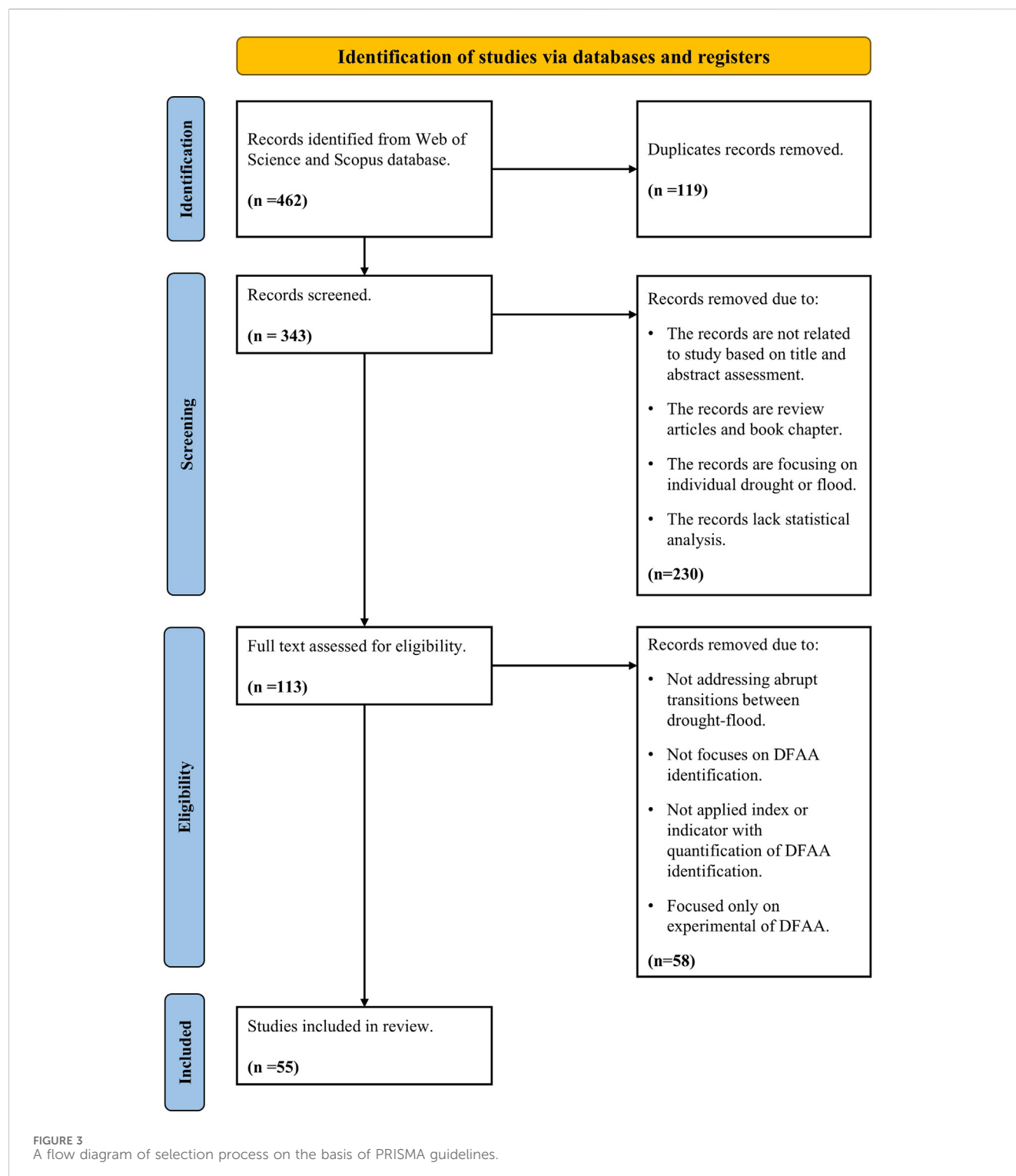
The identification process refined the search and narrowed the initial results to a manageable number. Three terms have been commonly used in the literature to describe the compound phenomenon of DFAA events (Bai et al., 2023): “Dry-wet abrupt alternation” (Shan L. et al., 2018; Yu et al., 2024), “Compound weather whiplash” (Ford et al., 2021; Francis et al., 2022) and “Lagged compound drought-flood” (Deng et al., 2024; Chen and Wang, 2022). The search terms comprised a combination of keywords associated with DFAA events, as shown in Table 2. The inclusion criteria were as follows: (1) DFAA-related articles published between 1 January 2000, and 31 December 2024; (2) studies in research areas related to meteorology, atmospheric sciences, water resources, physical geography, and agriculture; and (3) articles published in English. The initial search from SCOPUS and WoS yielded 200 and 262 articles, respectively.

After removing duplicates, the remaining 343 studies were screened based on their titles, abstracts, and keywords to assess their suitability according to the inclusion criteria. First, review articles and book chapters were excluded because they did not meet the criteria for empirical research. Second, studies focusing solely on individual drought or flood events without addressing compound or successive drought-flood events were excluded. Additionally, articles lacking statistical analysis were omitted to ensure the inclusion of studies with rigorous methodological approaches and quantitative data. In the subsequent eligibility screening, 58 articles were excluded to narrow the selection to studies that were most relevant to the objectives of this systematic review. Specifically, articles that studied abrupt transitions and alternations (key characteristics of DFAA) and those that applied indices to quantify and identify DFAA were included. In addition, articles using pot experiments that focused on crop responses within one or two growing seasons under controlled DFAA stress conditions were excluded, as their short-term and small-scale design had limited relevance to long-term and regional-scale DFAA identification. Finally, 55 articles were deemed eligible for inclusion in the systematic review.

4 Results and discussion

4.1 Geographical distribution and temporal trends in publications

Studies focusing on DFAA events have increased in recent years, as reflected by a notable rise in publication numbers (Mann-Kendall test, $p = 0.001$), particularly between 2019 and 2024 (Figure 4). This increase reflects the growing research attention to DFAA events, highlighting their significant threats to communities and ecosystems. Consequently, researchers have intensified their efforts to identify and characterize DFAA events. The increase in publications can be attributed to several factors, including growing concerns over DFAA events, advancements in data analysis techniques, and increased research funding in the context of climate change and disaster management.



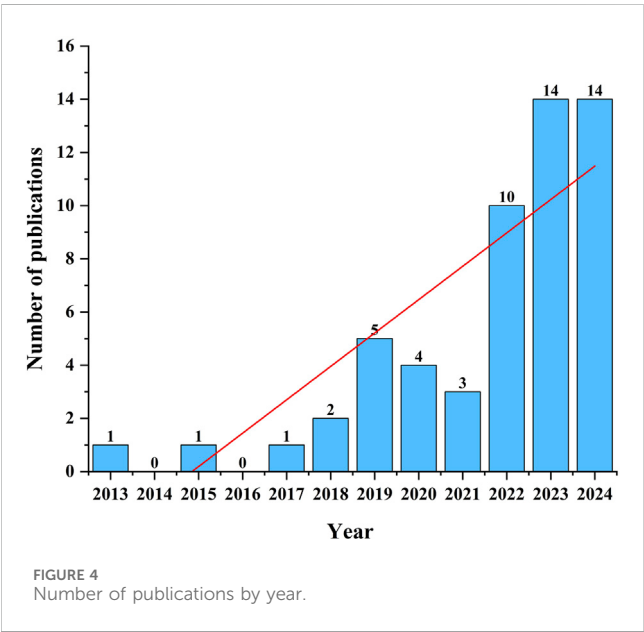
While most studies have been conducted at regional or national scales, global-scale research has increased since 2020, with six studies addressing DFAA events from a global perspective. Global-scale studies typically use coarse-resolution reanalysis datasets and drought-flood indices (e.g., SPI, SPEI, scPDSI) at the monthly scale to ensure cross-regional comparability and reveal hotspot distributions of DFAA events. At the regional scale, studies generally emphasize methodological flexibility by integrating

multiple data sources (e.g., meteorological and hydrological observations, and reanalysis datasets), adopting monthly-scale and daily-scale indices, and applying indices that better reflect regional hydroclimatic characteristics.

Regional-scale studies have predominantly focused on South Asia, Central Asia, and Asia as a whole, whereas national-level research has primarily concentrated in China, the United States of America, Canada, and South Korea (Figure 5). In these studies, those

TABLE 2 The search strings.

Database	Search queries
Web of Science	TOPIC: (Drought-flood abrupt alternation or Dry-wet abrupt alternation or Compound weather whiplash or Lagged compound drought-flood) Refined by: TOPIC: (Dry-wet sudden alternation or Dry-wet abrupt shift or Drought-flood sudden turns or Drought-flood abrupt transition or Weather whiplash or Precipitation whiplash or Successive dry-wet extremes or Drought-pluvial volatility)
Scopus	TOPIC: (Drought-flood abrupt alternation or Dry-wet abrupt alternation or Compound weather whiplash or Lagged compound drought-flood) Refined by: TOPIC: (Dry-wet sudden alternation or Dry-wet abrupt shift or Drought-flood sudden turns or Drought-flood abrupt transition or Weather whiplash or Precipitation whiplash or Successive dry-wet extremes or Drought-pluvial volatility)



conducted in monsoon-dominated regions (e.g., Korea, China, and South Asia) often employ daily-scale drought-flood indices (e.g., SPI, SWAP, SAPEI) and region-adapted DFAA indices (e.g., LDFAI, DWAAI, MSDFI) to identify DFAA events and capture their abrupt transitions. By contrast, studies in North America and Central Asia primarily use monthly drought-flood indices (e.g., SPI, SPEI) to analyze the frequency and intensity of DFAA events, which can reflect long-term DFAA trends but have limited ability to capture short-term abrupt transitions. Overall, regional-scale studies commonly adopt data- and index-based approaches to identify DFAA events.

However, as climate change continues to influence the distribution and intensity of extreme weather events, more regions are expected to face increased DFAA risk in the future. The predominance of DFAA studies in China (58%) can be attributed to region-specific climatic and geographic conditions that increase the occurrence and complexity of DFAA events, attracting considerable research attention. Nevertheless, such geographic concentration reflects the importance of expanding research efforts to diverse climates and terrains to deepen the overall understanding of DFAA phenomena. Accordingly, there is a critical need for region-specific approaches to DFAA identification that account for the interplay of factors such as climate, topographical features, and land use.

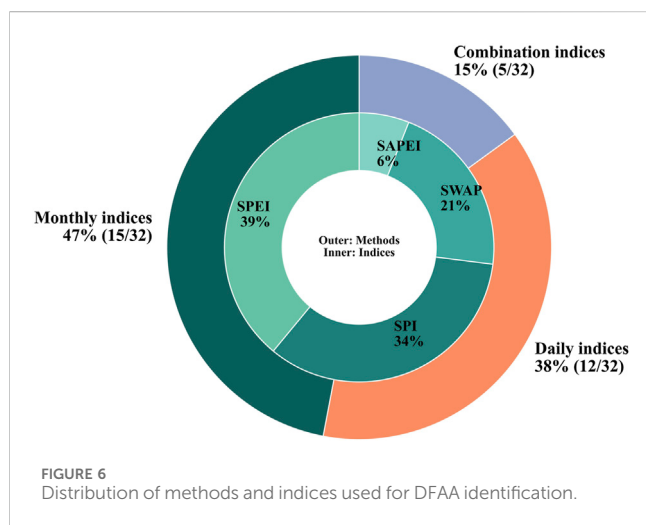
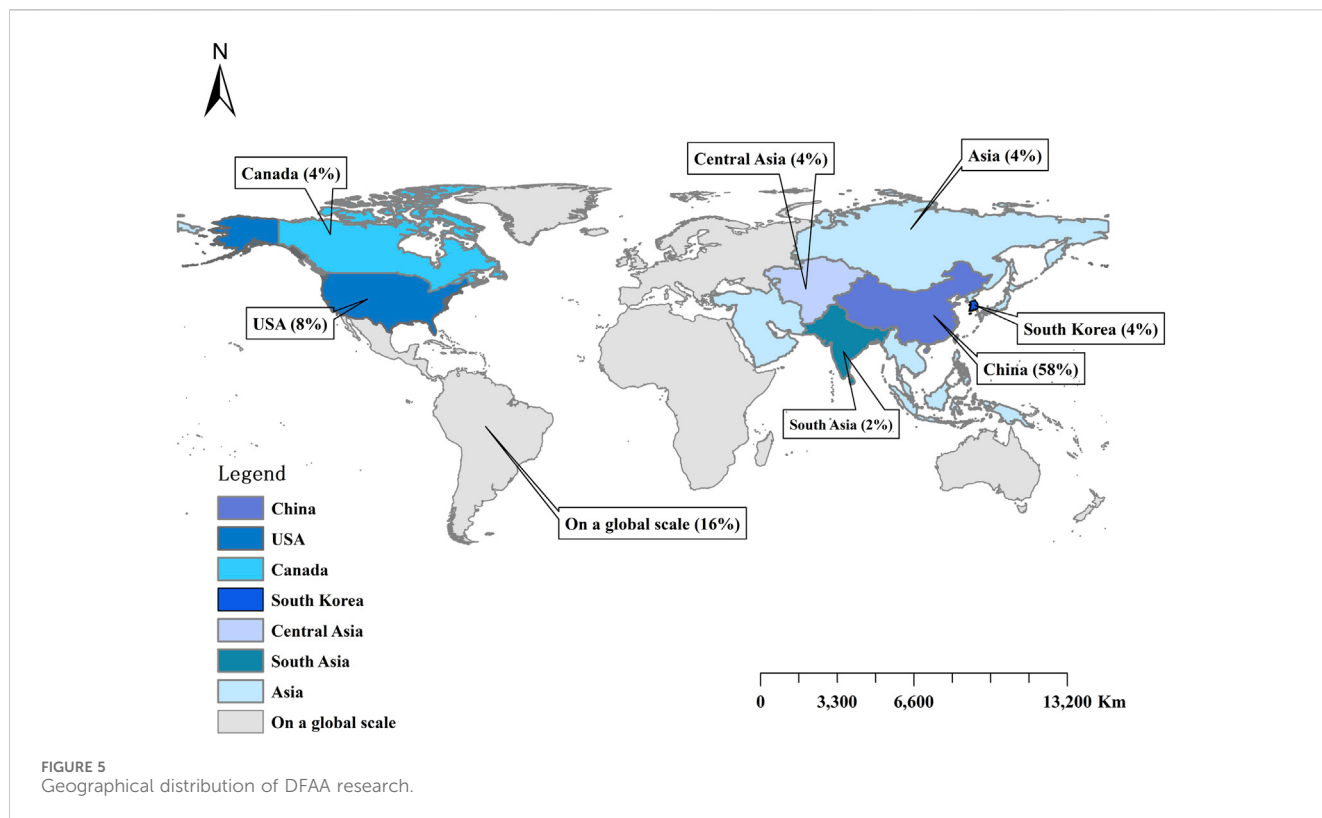
4.2 Methods for identifying and characterizing DFAA

4.2.1 Application of drought-flood indicators and indices

Based on the publications reviewed in this article, 32 of 55 studies utilized drought-flood indicators and indices to identify DFAA events, which were categorized into three types: monthly scale drought-flood indices (15 of 32, 47%), daily scale drought-flood indicators and indices (12 of 32, 38%), and a combination of drought-flood indicators and indices (5 of 32, 15%). Among the drought-flood indices, the most commonly applied were the SPEI (39%), followed by the SPI (34%), Weighted Average Precipitation Index (SWAP, 21%), and Standardized Antecedent Precipitation Evapotranspiration Index (SAPEI, 6%). The overall distribution of these methods and indices is illustrated in Figure 6, where the outer ring represents the proportions of different method types, and the inner ring shows the application frequencies of specific indices.

Among the 32 studies reviewed, 15 employed monthly-scale drought-flood indices, such as the SPI and SPEI, to directly identify DFAA events (Liu G. et al., 2024; Son et al., 2024). These indices define a DFAA event when consecutive months exhibit opposite conditions (e.g., drought in 1 month followed by flooding in the next, indicating a DTF event, or *vice versa*), emphasizing the frequency and intensity of drought and flood occurrences (Chen et al., 2020a; Li et al., 2022). Nonetheless, monthly-scale drought-flood indices based on fixed time scales and pre-defined change points often struggle to precisely identify DFAA events, as key characterization variables are overlooked, such as event duration, alternation points, and transition time.

In contrast, 12 publications utilized daily-scale drought-flood indicators and indices, including the SPI, SWAP, SAPEI, Standardized Anomaly (SA), and the Peak Over Threshold (POT), often in conjunction with the run theory to monitor DFAA events (Qian et al., 2023; Zhang et al., 2024; Fu et al., 2023; Rezvani et al., 2023). In studies of DFAA events, run theory plays a crucial role in identifying and characterizing event features through key time series analysis methods (Fu et al., 2023; Zhou et al., 2023). By setting predefined thresholds (such as those for droughts and floods), the start and end times of drought and flood events can be accurately determined, facilitating the identification of transition times and alternation points. Additionally, variables such as intensity, transition time, and alternation points enable a more precise characterization of DFAA events in the time domain. Unlike monthly-scale drought-flood indices, daily-scale indices and



indicators combined with run theory provide a more precise, event-based approach that emphasizes the transition time (measured in days). However, run theory may lack precision in quantifying transition speed, leading to less accurate descriptions of dynamic processes in DFAA events. In addition, run theory emphasizes temporal patterns and sequences, neglecting the quantification of the spatial extent of DFAA events.

Although less frequently, combinations of drought-flood indicators and indices have been used in the literature, namely the self-calibrating Palmer Drought Severity Index (sc-PDSI) with precipitation intensity thresholds, the number of consecutive

rainless days with precipitation intensity thresholds, and relative soil moisture with precipitation intensity thresholds (Yan et al., 2013; Bi et al., 2019; Wang L. et al., 2024). These methods often treat drought and flood events as independent phenomena, monitoring drought using drought indices and indicators such as the sc-PDSI, SPEI, or rainless days, and floods with different precipitation intensity thresholds. However, most existing identification methods treat drought and flood as independent events when identifying DFAA, rather than recognizing the drought-flood alternation as a unified event, resulting in an incomplete characterization of key dynamic features such as transition points, duration, and speed.

4.2.2 Development of new DFAA indices

The literature review includes 23 of the 55 studies using new DFAA indices, namely the long-cycle Drought-flood Abrupt Alternation index (LDFAI) (Yang et al., 2022), short-cycle Drought-flood Abrupt Alternation index (SDFAI) (Li et al., 2017), Dry-wet Abrupt Alternation Index (DWAAI) (Fan et al., 2019), Multi-scale Standardized DFAA Index (MSDFAI) (Wang H. et al., 2024), Multi-factor Standardized DFAA Index (MSDFI) (Bai et al., 2024), and Soil Moisture Concentration Index (SMCI) (Qiu et al., 2024). Among them, the most popular were LDFAI and SDFAI (16 out of 23, 70%), followed by daily DWAAI (4 out of 23, 17%). Unlike the approach of using drought-flood indicators and indices, the DFAA is identified as a single integrated event rather than two separate neighboring flood or drought events, with its frequency and intensity represented within a single index.

Wu et al. (2006) first proposed the LDFAI to evaluate drought-to-flood (DTF) and flood-to-drought (FTD) transitions based on

precipitation data in the middle and lower Yangtze River region. Building on LDFAI, Zhang et al. (2012) introduced SDFAI and applied it to the runoff variable over the Huaihe River Basin. LDFAI and SDFAI are straightforward, quantifiable indices that are widely used to identify DFAA events across various river basins (Zhang et al., 2019; Cui et al., 2022; Li et al., 2024). Compared to the LDFAI, the SDFAI refines the timescale from 2 months to 1 month, maintaining the fundamental equation structure of the LDFAI but adjusting the weighting coefficients. However, both indices rely on fixed alternation points, which increases the likelihood of misidentifying or overlooking DFAA events. Additionally, the variables used for characterization in the LDFAI and SDFAI are limited to intensity and frequency, further undermining their accuracy and applicability in capturing the complexity of DFAA events. Driven primarily by the need to enhance the applicability of characterization variables, improve analytical robustness, and better align with natural processes and management requirements, researchers have replaced standardized values with the SPI and extended the analysis timescale from 2 months to a seasonal scale (Shi et al., 2022; Song et al., 2023). This approach improves long-term trend detection in DFAA events but may overlook short-term events occurring within a few weeks and is sensitive to timescale selection.

To address the aforementioned issues, Shan et al. (2018) developed a daily-scale DWAAI based on the LDFAI and SDFAI. This index assumes that a DFAA event represents only the drought-to-flood (DTF) transition process, with a 44-day drought period and a 10-day flood period determined according to Lu (2009), who found that the influence of antecedent precipitation on the drought period decays exponentially and becomes negligible after 44 days. Although the daily-scale DWAAI introduces a new characterization variable to describe transition speed, it focuses exclusively on the DTF process, limiting its broader applicability. Moreover, the drought and flood durations of DFAA events may vary considerably across regions due to differences in precipitation patterns, antecedent soil moisture conditions, and hydrological responses, which may lead to misjudgement or omission of DFAA events. Consequently, only a few studies have used the DWAAI to identify DFAA events (Wang J. et al., 2021; Liu et al., 2023; Liu T. et al., 2024).

4.2.3 Variables for characterizing DFAA events

Based on the common definition of DFAA events, the use of characterization variables enhances the understanding of their dynamic processes by quantifying key aspects such as frequency, duration, intensity, severity, transition time, transition speed, and spatial extent, as summarized in Table 3. The table reveals significant differences in the usage frequency of various characterization variables in the studies, highlighting the varying emphasis placed on the different aspects of DFAA events. Frequency (100%) is the most commonly used variable, indicating its role as a core element in describing the dynamic features of DFAA events. Intensity (69%) had a relatively high usage rate, reflecting the focus on the impact of DFAA events. In contrast, transition time (24%), transition speed (9%), and alternation point (4%) were less frequently used, even though they are crucial for uncovering the abrupt alternation characteristics of DFAA events.

In addition, severity (5%) and spatial extent (7%), which are critical for evaluating the consequences of DFAA events, are rarely utilized. This suggests that current research primarily emphasizes temporal characteristics while paying less attention to consequence analysis and spatial distribution. The high usage rates of frequency (100%), duration (35%), and intensity (69%) indicate that current studies have largely focused on quantifying these characteristics. However, underutilized variables (e.g., alternation point, transition time, transition speed, severity, and spatial extent) may represent key areas for future research. Further exploration of the alternation point, transition time, and transition speed could reveal the intrinsic driving mechanisms of DFAA events, while an analysis of the spatial extent could provide more direct support for regional management and planning.

4.3 Advances in DFAA identification

Recently, the introduction of state-of-the-art methods for DFAA event identification has significantly improved the monitoring accuracy. Traditional methods, including widely used DFAA indices (e.g., LDFAI, SDFAI, and DWAAI) and drought/flood indices (e.g., SPI and SWAP), face limitations because they are generally based on a single variable (e.g., precipitation), which restricts the integration of multiple hydroclimatic factors. In addition, these methods are not well-suited to characterizing abrupt transitions, whereas newly developed approaches exhibit greater adaptability and precision across both monthly and daily scales. Table 4 presents a concise SWOT analysis synthesizing the internal strengths and weaknesses along with the external opportunities and threats of the three state-of-the-art DFAA identification indices, which could potentially provide valuable insights for future improvements.

Wang L. et al. (2024) developed the Multi-scale Standardized DFAA Index (MSDFAI), which monitors DFAA events on 1 and 2-month timescales based on SPI and introduces a transition speed as a key variable. Transition speed (V) is defined as the ratio of the total duration of a DFAA event to the transition time from the drought to flood peak or from flood to drought peak based on the SPI. The specific equations are as follows.

$$V_1 = \frac{2 \times T_s}{T_{\max} - T_{\min} + 1} (SPI(T_s)_i \leq -0.5 \cap SPI(T_s)_{i+1} \geq 0.5)$$

$$V_2 = \frac{2 \times T_s}{T_{\min} - T_{\max} + 1} (SPI(T_s)_i \geq 0.5 \cap SPI(T_s)_{i+1} \leq -0.5)$$

$$V_3 = 0 ((-0.5 < SPI(T_s)_i < 0.5) \cup (-0.5 < SPI(T_s)_{i+1} < 0.5))$$

where T_s is the selected timescale of the DFAA events, $T_{\max}$ and $T_{\min}$ denote the months corresponding to the flood peak and drought peak, respectively. V_1 represents the transition speed of DTF events, where the SPI in month i is ≤ -0.5 (indicating drought), and the SPI in the following month ($i+1$) is ≥ 0.5 (indicating flood); V_2 corresponds to FTD events, where the SPI in month i is ≥ 0.5 (flood), and the SPI in the following month ($i+1$) is ≤ -0.5 (drought); V_3 represents non-DFAA events, where the SPI values in both month i and the following month ($i+1$) are between -0.5 and 0.5 , indicating non-flood and non-drought conditions. The MSDFAI incorporates transition speed to filter out the impact of

TABLE 3 List of characterizing variables of DFAA used in different publications.

Characterization variables	Description	Mathematical formula	Variables used in study (%)	Related references
Frequency	The number at which DFAA events occur	$F = \sum_{t=1}^T \delta(t)$ where $\delta(t) = 1$ if event occurs at time t	100	Fang et al. (2019), Zhao et al. (2020), Qiao et al. (2022a)
Duration	The length of time during which a DFAA event lasts	$D = t_{end} - t_{start}$ where t_{start} and t_{end} are DFAA start and end times	35	Qian et al. (2023), Chen et al. (2020a), Wang et al. (2023)
Alternation point	The specific time when the shift from drought to flood (or <i>vice versa</i>) occurs	AP = specific time point when transition happens	4	Liu G. et al. (2024), Shi et al. (2024)
Transition time	The timespan between the end of the former event and the start of the latter event in a DFAA.	$T = t_{AP} - t_{start}$ where t_{AP} is the time of the alternation point (AP), and t_{start} is the start time of the drought or flood period	20	Rahimimovaghar et al. (2024), Shi et al. (2021), Rezvani et al. (2023)
Transition speed	The rate of change in index during the transition process, that is, the magnitude of change in drought-flood index values per unit of time	$V = \frac{\Delta S}{T}$ where ΔS denotes the change in the DFAA index value, and T represents the transition time	9	Wang J. et al. (2021), Yu et al. (2024), Wang H. et al. (2024)
Intensity	The magnitude of the abrupt transition between drought and flood states	$I = f$ (DFAA index values) where f represents functions applied to the DFAA index values to quantify the event's intensity	69	Ji et al. (2018), Ren et al. (2023), Qiao et al. (2022b)
Severity	The overall magnitude and cumulative extremity of DFAA events	$S = \sum_{t \in N} X_t - T + \sum_{t \in M} X_t - T $ where X_t represents the value of an index at time t , T is the thresholds for drought and flood, N denotes the drought duration, and M is flood duration	5	Qiao et al. (2022a), Zhang B. et al. (2023), Bai et al. (2024)
Spatial extent	The geographic area affected by DFAA events, measuring the spatial distribution of the DFAA event occurrences	$E = \sum_{i=1}^N A_i$ where N denotes the total number of all DFAA events, A_i represents the area affected by the i th DFAA.	7	Fang and Lu (2023), Li et al. (2022), Bi et al. (2023)

TABLE 4 SWOT analysis of state-of-the-art indices for DFAA identification.

Index	MSDFAI	MSDFI	SMCI
Strength (S)	Introduces transition speed to effectively quantify the abruptness of DFAA events. Ensures broad applicability due to a simple SPI-based structure and widely available monthly precipitation data	Integrating multiple variables to capture both meteorological and soil moisture-driven drought-flood conditions, enhancing the comprehensiveness. Incorporates lagged response time, improving the accuracy in capturing the temporal dynamics of DFAA events	Quantifies daily soil moisture within a defined time window, enabling detection of short-term DFAA events. Can be cross-validated using SMA to enhance the reliability of identification
Weakness (W)	Relies solely on precipitation and monthly-scale indices, lacking integration of key hydrometeorological variables and the capacity to capture rapid transitions at daily timescales	Highly sensitive to the accuracy of estimated response time, introducing uncertainty. As a monthly-scale index, it lacks characterization variables for abrupt transition features, limiting its ability to accurately identify DFAA events	Does not include transition speed, reducing its capacity to describe the abruptness of DFAA. Relies on soil moisture, which could not fully capture DFAA events due to its lag and limited reflection of key hydrometeorological variables
Opportunity (O)	Incorporating more variables (e.g., temperature, evapotranspiration, and runoff) and daily-scale data (e.g., from remote sensing or reanalysis sources) can improve the accuracy of DFAA identification	Using finer temporal resolution data (e.g., daily or sub-monthly) and incorporating variables for abrupt alternation could strengthen event characterization. Incorporating region-specific response time estimation could enhance the spatial robustness of MSDFI.	Integrating transition speed and multivariable (e.g., precipitation, evapotranspiration, runoff) into SMCI, along with multi-source cross-validation using satellite (e.g., SMAP) and reanalysis (e.g., ERA5) data, possibly enhance the accuracy and reliability of DFAA identification
Threats (T)	Limited applicability in data-scarce or poor-quality data regions. Simplified transition speed based on drought-flood peak timing might not adapt to climate non-stationarity and rising extremes	High computational demands (e.g., multi-step normalization, copula modeling, and response time estimation) and dependence on high-quality, multi-source data could potentially pose challenges to the feasibility and applicability of MSDFI in data-scarce regions	Limited availability of multi-source datasets, the regional variability in soil moisture data quality, and the complexity of incorporating multiple variables into SMCI may hinder its practical implementation and reduce its accuracy in identifying DFAA events

individual drought and flood events, which better captures the abruptness of the DFAA. Nevertheless, in regions with insufficient or poor-quality precipitation data, transition speed may fail to accurately represent the abrupt transition nature between drought and flood. Moreover, because the SPI is based solely on precipitation, it is more suitable for tropical regions with relatively stable temperatures and low evapotranspiration variability (Kim et al., 2023); however, it potentially underestimates drought and flood intensity in arid regions (Wang W. et al., 2021), leading to regional biases in transition speed across different climate zones.

Bai et al. (2024) proposed a Multi-factor Standardized DFAA Index (MSDFI) to describe DFAA events, incorporating rainfall, evapotranspiration, and soil moisture. The optimal response time (RT) was determined by calculating the Pearson correlation between the monthly SPEI and the Standardized Soil Moisture Index (SSMI). Then, a copula function is used to obtain the standardized SDMI using SPEI-RT and 1-month SSMI, which is ultimately used to construct the MSDFI, as formulated below.

$$MSDFI = \frac{SDMI_{i+RT} - SDMI_i}{2} \left(1 + \frac{|SDMI_{i+RT} - SDMI_i|}{R} \right)$$

$$(i = 1, 2, \dots, n)$$

Where $SDMI_i$ is the SDMI value of the i th time series, $SDMI_{i+RT}$ is the SDMI value at $i + RT_{th}$, R is the deviation between the maximum SDMI and minimum SDMI in the same pixel, and n is the sequence length. The MSDFI is a composite index that combines the meteorological SPEI and soil SSMI using Pearson's correlation, enhancing the accuracy of DFAA event identification from a multi-factor perspective and making it a robust index for studying DFAA events. However, its computational complexity and RT dependency limit its applicability to short-term DFAA events under complex conditions.

Qiu et al. (2024) proposed a daily-scale Soil Moisture Concentration Index (SMCI) based on soil moisture. The SMCI quantifies and normalizes the deviation between the actual soil moisture accumulation curve $f_1(t)$ and the assumed uniform accumulation curve $f_2(t)$ within a fixed-length window ($L = 2T + 1$, where T is the half-window length) and is calculated as follows:

$$SMCI = \frac{\int_{i-T}^{i+T} [f_1(t) - f_2(t)] dt}{\int_{i-T}^{i+T} f_2(t) dt}$$

The SMCI reflects the deviation of actual soil moisture changes from an assumed uniform distribution and better characterizes the dynamic characteristics of soil moisture. SMCI serves as a key indicator for identifying potential DFAA events and further validates these events through soil moisture anomalies (SMA), thereby improving the accuracy of DFAA event identification. The SMCI focuses on characterizing the dynamic characteristics of short-term soil moisture, but its lack of transition speed quantification and reliance on soil moisture data make it challenging to accurately distinguish the influence of other important climate factors on DFAA event identification during the abrupt transition between drought and flood.

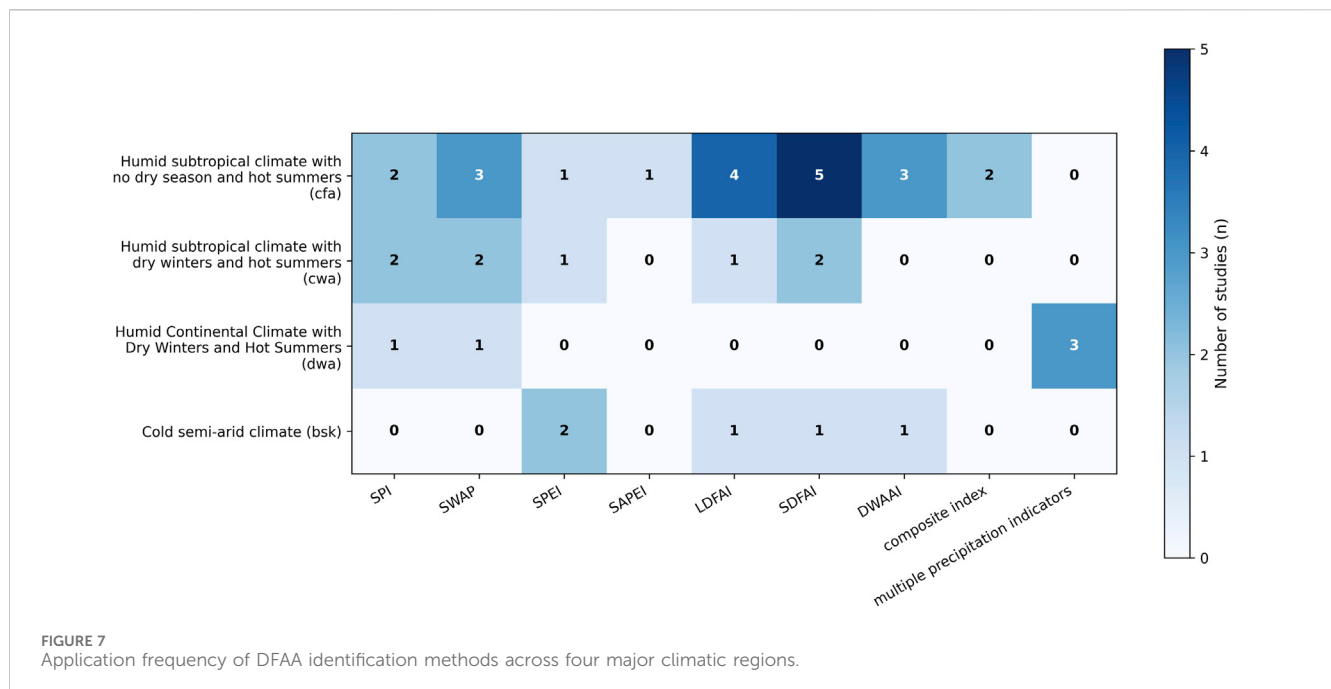
4.4 Climatic drivers of DFAA events

Figure 7 illustrates the application frequency of different DFAA identification methods across the four major climatic regions, classified based on the Köppen–Geiger climate classification, after excluding 16 studies whose research areas spanned multiple climatic zones. As shown in the figure, precipitation-based indices dominated DFAA identification (Cfa: $n = 17$; Cwa: $n = 7$; Dwa: $n = 5$; Bsk: $n = 3$), reflecting the primary importance of precipitation in driving DFAA events. Nevertheless, a few studies in the Cfa ($n = 4$), Bsk ($n = 2$), and Cwa ($n = 1$) climate regions utilized indices that integrated other hydro-meteorological variables, such as temperature, potential evapotranspiration, relative humidity, and soil moisture. Notably, the relatively more frequent use of SPEI ($n = 2$) in semi-arid climate zones highlights the significant role of temperature and potential evapotranspiration as key drivers of DFAA.

The forest plot in Figure 8 presents the results of a random-effects meta-analysis examining the relationships between major climatic drivers and DFAA events based on 18 studies ($k = 18$) reporting correlation estimates. The meta-analysis revealed a weak pooled correlation between DFAA and climatic factors ($r = 0.060$, $p = 0.572$). Subgroup analyses indicated that ENSO showed highly consistent effects with negligible heterogeneity ($I^2 = 0\%$), but its pooled correlation with DFAA events was not statistically significant. Although precipitation, temperature, and potential evapotranspiration exhibited high heterogeneity ($I^2 > 90\%$), potential evapotranspiration and temperature were significantly negatively correlated with DFAA events, whereas precipitation was significantly positively correlated. The high heterogeneity indicates that the influence of climatic drivers on DFAA events is highly region-dependent, a pattern that was further confirmed by subgroup analyses.

The meta-analysis results and method application patterns collectively highlight that the dominant climatic drivers of DFAA events and the effectiveness of different identification methods are largely context-dependent. In humid subtropical climates (Cfa and Cwa), precipitation serves as the primary driver of DFAA events. In particular, changes in temporal precipitation concentration have strong influence in Cwa regions with pronounced seasonal contrasts, while short-term precipitation anomalies play a more prominent role in Cfa regions. Therefore, indices that are sensitive to short-term temporal variations and can effectively capture abrupt drought-flood alternations are recommended for both climates. Moreover, in karst regions within the Cfa climate zone, geomorphological complexity leads to distinct hydrological responses to precipitation, with intense rainfall and shallow rocky soils leading to rapid infiltration and quick drought-flood transitions (Fan et al., 2019; Dai et al., 2023). Hydrological modeling may help address the limitations of precipitation-based indices by representing surface-subsurface interactions, infiltration-runoff processes, and hydrological responses, thereby improving the identification of DFAA events.

In humid continental climates (Dwa), precipitation remains the main driver of DFAA events, while temperature also plays an important role by regulating effective precipitation through processes such as snowfall, snowmelt, and evapotranspiration (Bi et al., 2019). In such regions, DFAA indices that incorporate runoff,



soil moisture, or water storage can complement meteorological indices by capturing the delayed and integrated responses of the hydrological system. Precipitation and potential evapotranspiration are key factors controlling DFAA events in Bsk climate zone (Qiu et al., 2024; Zhu et al., 2025), and indices such as the SPEI and SAPEI, which incorporate precipitation and potential evapotranspiration, may be better suited for capturing DFAA events. Taken together, identification approaches that account for region-specific climatic drivers and integrate multiple variables may be crucial for improving the accuracy of DFAA detection.

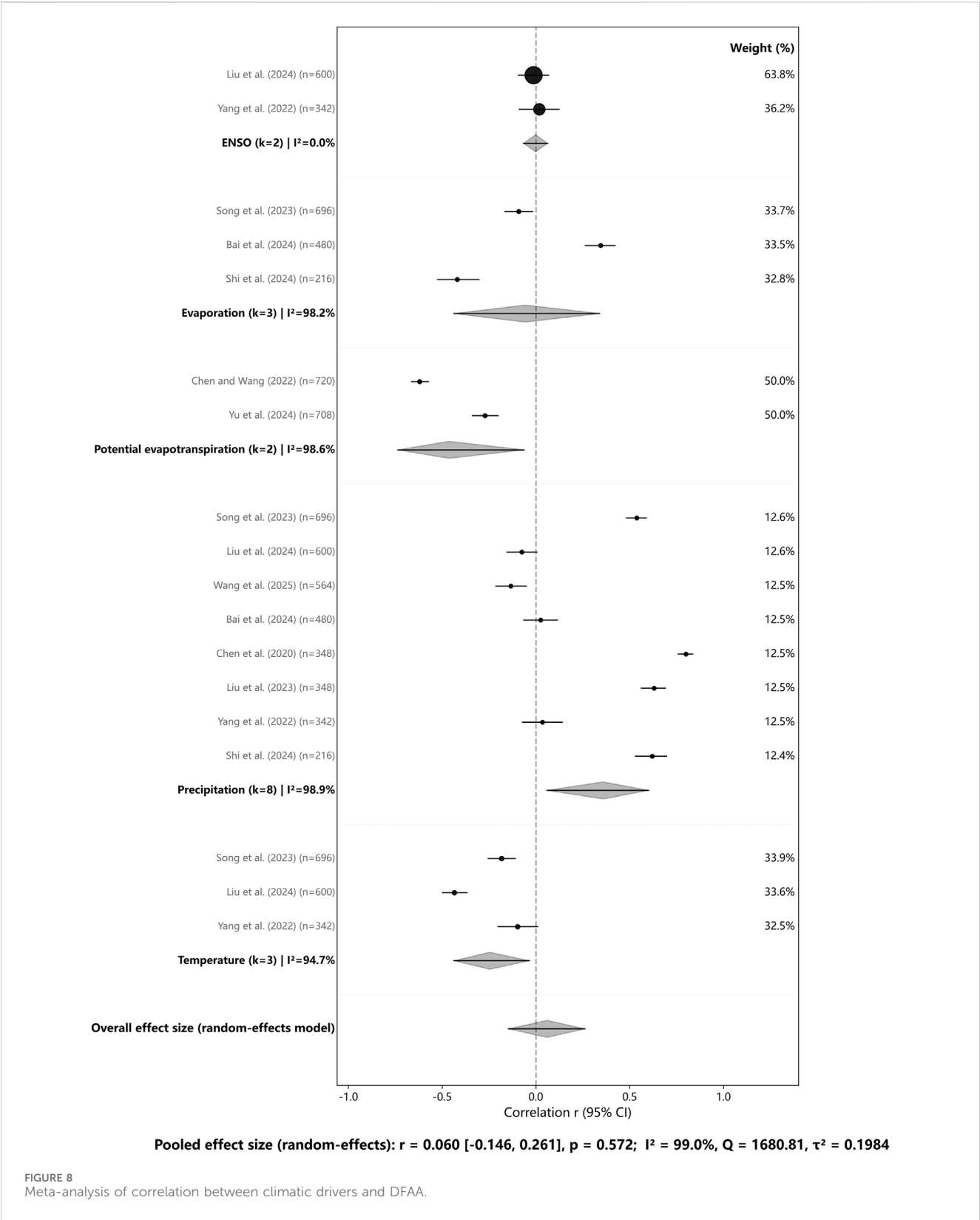
5 Future directions for identifying DFAA under climate change

Climate change is projected to influence the water cycle (Jain et al., 2024) by enhancing evaporation and increasing atmospheric water vapor content, potentially leading to more days without precipitation and more intense rainfall, which could affect the occurrence of DFAA events (Madakumbura et al., 2019; Kendon et al., 2019). Studies have shown that drought and flood events have intensified across all climate regions, with greater amplification of extremes in areas where seasonal water variability is more pronounced, and these events often coincide at 1-month intervals (Tabari, 2020; Jun and Rind, 2024; Heim et al., 2023; Dhawale et al., 2024). Additionally, Deng et al. (2024) project that under climate scenarios such as SSP2-4.5 and SSP5-8.5, these coincidence rates could rise further. By the end of the century, model projections suggest that global DFAA events could increase by about 2.56 ± 0.16 times, particularly in monsoon-dominated regions such as East Asia, South Asia, and East Africa, highlighting the need for region-specific identification standards and methodologies (Chen and Wang, 2022; Tan et al., 2023; Fang and Lu, 2023).

5.1 Enhancing regional DFAA identification through multi-source data

Under the influence of climate change, regional DFAA events have become more complex and variable, rendering traditional ground-based station data insufficient for accurate DFAA identification (De Sherbinin et al., 2019; Sun et al., 2024). Reanalysis datasets (e.g., ERA5, MERRA, and NCEP) are widely used as a complement to ground-based observations because of their broad spatial coverage and continuous temporal records (Katipoğlu, 2023). Nonetheless, studies have shown that assessing the incidence and intensity of droughts and floods using reanalysis datasets is challenging in regions like Ethiopia, where ground-based observational data are scarce (Berhanu et al., 2024). Given this, remote sensing data (e.g., TRMM precipitation at the monthly scale, MODIS land surface temperature, and SMAP soil moisture), combined with reanalysis datasets, may help address data gaps in drought and flood identification (Huang et al., 2021), although nonsystematic biases and underestimation of short-term variability may still persist.

Moreover, remote sensing imagery, such as the Normalized Difference Water Index (NDWI), Modified NDWI (MNDWI), and Normalized Difference Vegetation Index (NDVI) derived from MODIS, Landsat, or Sentinel-2, can indirectly reflect drought and flood events by monitoring rapid changes on the land surface (Thapa et al., 2022; Magnússon et al., 2023). For example, NDVI can indicate drought and flood through the rapid withering or submersion of vegetation within a short time period (Ullah et al., 2023). Therefore, integrating multi-source datasets can substantially improve the spatial and temporal precision of identifying abrupt transitions between drought and flood, particularly in regions with scarce or low-quality ground-



based observations. However, remote sensing products such as Sentinel-2 (5-day revisit) and Landsat (16-day revisit) have relatively long revisit cycles and are susceptible to cloud contamination, which reduces their effective observation

frequency. As a result, abrupt transitions lasting several days to weeks in DFAA events may fail to be captured.

Furthermore, long-term, continuous, and multivariable outputs from climate models provide a valuable basis for exploring future

DFAA risks, but their inherent uncertainties pose significant challenges. Atmospheric circulation and sea surface temperature anomalies, including the Intraseasonal Oscillation (ISO), Pacific Decadal Oscillation (PDO), Arctic Oscillation (AO), and ENSO, play critical roles in shaping DFAA events, although local hydrometeorological factors remain the primary drivers (Zong et al., 2012; Yuan et al., 2021; Shi et al., 2023; Wang H. et al., 2024). To incorporate these large-scale influences, regional hydrological models (e.g., VIC and SWAT) can indirectly account for atmospheric circulation processes when integrated with climate model outputs, even though they are primarily designed to simulate detailed hydrological processes (Zhang and You, 2018; Bao et al., 2025). Thus, coupling climate models with hydrological models could improve simulations of regional hydrometeorological processes, thereby enhancing understanding of potential DFAA risks under different scenarios. However, due to substantial uncertainties in both climate and hydrological models, their outputs are better suited for conducting scenario-based risk analyses of future DFAA events rather than for deterministic predictions.

5.2 Potential improvements for identifying DFAA events

Monthly-scale indices rely on monthly data, which are easily accessible and offer wide spatial coverage, providing a good basis for analysing long-term trends in DFAA events. In comparison, daily-scale indices can better capture the abrupt nature of DFAA but may suffer from data incompleteness or quality instability in complex terrains. Consequently, constructing composite indices that integrate multiple variables and timescales can improve the robustness of DFAA identification. When combined with run theory, daily-scale indices can effectively detect alternation points and transition times of DFAA events. Nevertheless, run theory may fail to capture flash droughts and flash floods, which are characterized by rapid onset and short duration, because it relies on cumulative sequences. Hence, future studies could benefit from integrating high-frequency precipitation data (e.g., sub-daily precipitation) to better capture flash droughts and flash floods within DFAA events. However, leveraging such high-frequency precipitation data would require more sophisticated modeling frameworks and may introduce additional uncertainties.

Existing research has demonstrated that machine learning (ML) and deep learning (DL) models (e.g., Long Short-Term Memory, Convolutional Neural Network, and Generative Adversarial Network) can dynamically adjust the length of time windows based on variations in temporal series to capture the short-duration characteristics of flash droughts (Zhang et al., 2022; Barbosa et al., 2024; Foroumandi et al., 2024). In this context, a dynamic time window, determined through DL and ML models, is used to adaptively expand during stable periods and contract around abrupt shifts to dynamically adjust timescales for identifying DFAA events. This approach is expected to improve the accuracy of DFAA identification and partially address the limitations of conventional monthly and daily scale indices; however, properly quantifying uncertainty remains essential for robust applications.

In addition, previous studies have applied bias correction and downscaling techniques (e.g., Random Forest, Empirical Quantile

Mapping, and dynamical downscaling) to refine CMIP5 and CMIP6 outputs for identifying DFAA events under future climate scenarios (Chen et al., 2020b; Rezvani et al., 2023; Liu G. et al., 2024). However, these approaches generally assume that the statistical properties of model errors remain constant over time and provide deterministic estimates without explicitly quantifying prediction uncertainty. The Bluecat method, proposed by Koutsoyiannis and Montanari (2022a), can upgrade deterministic outputs from GCMs, SWAT, and most ML/DL models into stochastic predictions, enabling explicit quantification of prediction uncertainty. Building on this framework, the extended Bluecat (e-Bluecat) further preserves climate-change signals from GCM projections while simultaneously correcting biases and quantifying uncertainty (Koutsoyiannis and Montanari, 2022b; Santos et al., 2025). Although uncertainties remain, the Bluecat and e-Bluecat provide a complementary framework for refining GCM projections, offering valuable insights into potential future changes in DFAA events.

DFAA events often exert greater impacts than individual drought or flood events, and the rapid alternation between drought and flood within a short period compresses the available time for early warning and emergency response, posing substantial challenges for disaster prevention and mitigation departments, especially in densely populated and low-income regions of developing countries. However, as less than 10% of current DFAA studies incorporate variables describing the spatial extent and severity of events, the capacity to conduct comprehensive disaster impact assessments remains limited, thereby constraining our understanding of population exposure, economic losses, and cascading impacts. To address these compound risks, future efforts should establish integrated disaster management strategies that combine monitoring, early warning, and emergency response in vulnerable regions, while accounting for key hydroclimatic drivers of DFAA events.

Moreover, enhancing resilience to DFAA events requires interdisciplinary collaboration—spanning climate science, agriculture, water resource management, and social policy—together with data-driven approaches that integrate meteorological, hydrological, and socio-economic data to support dynamic risk tracking and improve early warning responsiveness. Specifically, national meteorological agencies should incorporate DFAA characteristics (e.g., severity, spatial extent, transition time, and transition speed) into existing early warning systems to enhance detection and response capabilities. Meanwhile, agricultural and emergency management departments should develop differentiated response strategies and long-term adaptation plans based on identified DFAA risks, thereby strengthening the linkage between pre-disaster preparedness and post-disaster recovery to improve overall system resilience. Therefore, future research should strengthen the scientific foundation for DFAA risk management by conducting comprehensive risk assessments across diverse socio-economic contexts, thus providing a robust basis for more integrated DFAA governance in the context of a changing climate.

6 Conclusion

In this review, we synthesize 55 publications, providing a systematic and unbiased analysis of DFAA event identification methods. Our findings underscore the necessity of standardized

terminology to define DFAA events, emphasizing their abrupt nature and regional consistency. To address this, we summarize a unified framework that categorizes key terms into transition direction, alternation point, transition time, and geographical consistency, where alternation point and transition time specifically reflect the abruptness of DFAA events. Research on DFAA events has increased significantly in recent years, with China leading in the number of studies, followed by the United States and Canada.

In terms of DFAA identification, 58% of studies adopt traditional drought-flood indices and indicators, whereas 42% propose novel DFAA indices. From another perspective, the studies of DFAA characterization focus primarily on fundamental variables such as frequency, intensity, and duration but tend to overlook the abrupt alternation dynamics between drought and flood, including alternation point, transition time, and transition speed. Traditional monthly-scale drought-flood indices predefine alternation points and operate on long timescales, making them less effective in capturing abrupt transitions. In contrast, traditional daily-scale indicators and indices define alternation points and transition time more precisely using run theory and thresholds, though they do not quantify transition speed.

Unlike drought-flood indicators and indices, emerging DFAA indices treat DFAA as a single integrated event rather than two separate occurrences, with its frequency and intensity captured in one index. Among them, monthly-scale LDFAI and SDFAI are widely used for their simplicity and quantifiability but are still constrained by fixed alternation points and fail to quantify the abrupt nature of DFAA, which can lead to misidentification and omission. In contrast, the daily-scale DWAAI incorporates transition speed as a new variable to quantify the transition time of DFAA, further indicating the abruptness of change in DFAA events. However, DWAAI does not account for the transition direction of DFAA events, as it exclusively focuses on DTF while neglecting FTD transitions.

This review evaluates advanced methods for DFAA identification, highlighting their respective strengths and limitations. The monthly-scale MSDFAI introduces transition speed and helps mitigate the influence of isolated drought and flood events but lacks sensitivity to daily-scale variations and relies solely on precipitation. MSDFI integrates multiple indices to enhance detection but still struggles to capture abrupt transitions. In contrast, SMCI enables daily-scale identification and validation via SMA; however, it cannot quantify transition speed and depends entirely on soil moisture, which limits its broader applicability. Furthermore, while precipitation is the dominant driver of DFAA events, temperature and potential evapotranspiration play critical roles in arid and semi-arid regions. Meta-analysis reveals significant positive correlations with precipitation and negative correlations with temperature and evapotranspiration, although these relationships are highly region-dependent.

Traditional ground-based observations alone may not fully capture the complexity of regional DFAA events under climate change, rendering reanalysis datasets and remote sensing products valuable complementary sources, despite their inherent limitations such as biases, long revisit cycles, and cloud contamination. Machine learning (ML) and deep learning (DL), together with dynamic time windows and composite indices, offer strong potential to enhance the accuracy and robustness of DFAA identification. Bias correction, downscaling, and emerging stochastic frameworks such as Bluecat and e-Bluecat further refine GCM outputs for future DFAA assessment by preserving climate signals and explicitly

quantifying prediction uncertainty. Moreover, DFAA events often have greater impacts than individual droughts or floods, as rapid alternation shortens early warning and emergency response times. However, limited consideration of event severity and spatial extent restricts comprehensive risk assessments and understanding of cascading impacts. Strengthening resilience requires integrated management strategies, interdisciplinary collaboration, and data-driven approaches to improve early warning and adaptive governance under climate change.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

LZ: Conceptualization, Formal Analysis, Investigation, Writing – original draft, Writing – review and editing. KA: Conceptualization, Methodology, Supervision, Writing – review and editing. FA: Conceptualization, Supervision, Writing – review and editing. LC: Supervision, Visualization, Writing – review and editing. MS: Investigation, Methodology, Visualization, Writing – review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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