Water and Soil Management and Modeling

University of Mohaghegh Ardabili

Online ISSN: 2783 - 2546

A systematic review of performance assessment in canal irrigation systems: Integrating socio-technical, remote sensing, and AI-driven approaches for a climate-resilient future

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Abstract

This systematic review investigates the evolution of performance assessment in canal irrigation systems globally, drawing evidence from Asia, Africa, and Latin America. Adhering to PRISMA guidelines, it synthesized 98 peer-reviewed studies and key organizational reports published between 1990 and 2025, primarily from Scopus and Web of Science. The analysis reveals a clear methodological progression from direct measurements to remote sensing (RS) and agro-hydrological modeling, with Artificial Intelligence (AI) now evidenced as an applied tool in some assessments, not merely a prospect. A critical insight, however, is that despite these technical advancements, persistent underperformance is primarily rooted in deep-seated non-technical (financial, institutional, social) barriers. The current review highlights a significant gap: the absence of a unified framework systematically integrating these technical and socio-institutional dimensions with forward-looking climate resilience. Our primary contribution is a novel, integrated socio-technical assessment framework designed to bridge this divide. Distinct from previous reviews, the proposed framework explicitly combines the methodological triad, comprehensive socio-institutional analysis, quantifiable climate resilience metrics, and mechanisms to ensure social equity in AI-driven management. This adaptable, multi-scale diagnostic tool offers an actionable blueprint, applicable from local canal management to national policy levels, that accounts for diverse regional data limitations. By enabling more effective problem diagnosis and intervention design, the proposed framework provides significant analytical value and actionable lessons for enhancing the productivity, equity, and climate resilience of canal irrigation systems, thereby directly advancing Sustainable Development Goals 2 and 6.

Keywords: Agro-hydrological modelling, AI and ML, Climate change, Direct Measurement, Performance evaluation.

Article Type: Review Article

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Citation: Rajaput, M., Abhilash, R., & Dodamani, B. M. (2025). A systematic review of performance assessment in canal irrigation systems: Integrating socio-technical, remote sensing, and AI-driven approaches for a climate-resilient future, Water and Soil Management and Modeling, 5(4), 254-276.

doi: 10.22098/mmws.2025.18343.1683

Received: 17 September 2025, Received in revised form: 03 October 2025, Accepted: 20 October 2025, Published online: 07 November 2025

Water and Soil Management and Modeling, Year 2025, Vol. 5, No. 4, pp. 254-276.

Publisher: University of Mohaghegh Ardabili

1. Introduction

1.1. The enduring challenge

Canal irrigation systems are a cornerstone of global food production. While irrigated land constitutes only 20% of global cropland, it is responsible for a remarkable 40% of the world's food supply, highlighting its profound impact on agricultural productivity (Schultz et al. 2005). In many arid and semi-arid nations, these systems are the lifeblood of agriculture, with irrigation accounting for over 90% of total freshwater withdrawals (UNESCO, 2021). This intensive water use places canal irrigation at the center of a critical tension between two of the United Nations' Sustainable Development Goals: SDG 2 (Zero Hunger), which demands increased food production, and SDG 6 (Clean Water and Sanitation), which calls for sustainable water management and improved water-use efficiency across all sectors (IFPRI, 2019; UN, 2022).

1.2. The pervasive "performance gap": a quantified challenge

Despite their importance, a persistent and well-documented "performance gap" exists in many canal systems, where actual performance falls drastically short of design potential (Molden, 2013; Ward et al., 2024). This is not a minor issue; it is a systemic failure with significant quantitative dimensions. Globally, the overall efficiency of many canal systems languishes between 30% and 50%, meaning that up to 70% of the water diverted is lost before reaching the crop root zone due to a combination of physical losses (seepage, evaporation) and managerial inefficiencies (FAO, 2020; Jägermeyr et al., 2015). This chasm between design and reality is starkly illustrated in regions like South Asia, where conveyance efficiencies in some large-scale systems have been measured at less than 40% (Rasul, 2016) The consequences are direct and severe; a yield gap where actual agricultural production is 30-50% lower than its potential (FAO & DWFI, 2015), inequitable water distribution that leaves tail-end farmers with chronic shortages, and accelerated infrastructure decay (Kori & Umesh, 2020; Kulkarni, 2020; Yapa et al., 2020).

Furthermore, climate change is no longer a future threat but a present reality, directly exacerbating this performance gap. Recent studies from river basins across the world demonstrate tangible impacts: a meta-analysis by Woznicki et al. (2015) projected that irrigation demands could increase by over 40% in some regions due to rising temperatures (Woznicki et al., 2015), while recent works on changing climate showed a **15% reduction in water availability for irrigation** due to altered precipitation patterns (Orkodjo et al., 2022; Rosa & Sangiorgio, 2025). These climatic shifts place unprecedented stress on already underperforming systems, making performance assessment and improvement an urgent priority.

1.3. The evolving landscape of performance assessment

The methods used to diagnose and address these performance gaps have evolved significantly. Early assessments were dominated by a narrow, engineering-centric focus on hydraulic efficiency, relying on direct, field-based measurements (Bos & Nugteren, 1990). A paradigm shift began in the late 20th century, marked by the development of more holistic evaluation frameworks that recognized irrigation systems as complex socio-technical entities. These foundational frameworks broadened the scope of assessment to include agricultural, economic, and social dimensions, providing the intellectual bedrock for modern performance analysis. As summarized in Table 1, three frameworks were particularly influential in this shift. Small & Svendsen (1990) introduced a "nested systems" framework, conceptualizing irrigation as a series of interconnected systems where the output of one (e.g., water delivery) becomes the input for the next (e.g., agricultural production), extending all the way to the national socio-economic system. This highlighted the multifaceted purposes of irrigation beyond simple water conveyance. Building on this, Murray-Rust & Snellen (1993) framed performance assessment as a diagnostic tool for management, emphasizing the use of outputs to identify opportunities for improvement across the entire management cycle, rather than as an end in itself. Later, Bos et al. (2005) proposed a systematic, staged process that aligns the assessment's purpose, indicators, and data collection methods, ensuring that evaluations are not only data-informed but also actionable for managers and stakeholders. This evolution in conceptual thinking reflects a broader shift in development practice from a focus on constructing physical infrastructure to a more nuanced understanding of the institutions, policies, and human factors that govern its success.

A review of the literature reveals that many prior syntheses on this topic have been largely narrative, offering fragmented summaries rather than a systematic analysis of methodological trends and persistent knowledge gaps. For instance, reviews like that of Pereira et al. (2012) provided on-farm analysis using indicators, while Muturi et al. (2025) focused narrowly on specific techniques like remote sensing, whereas Elshaikh et al. (2018) focused without integrating them into a broader socio-technical context. The current review addresses this deficiency by employing the PRISMA (Preferred Reporting Items for Systematic reviews and Meta-Analyses) methodology to systematically chart the evolution from traditional methods to modern, technology-driven approaches.

1.4. Research gaps and the emergence of new technologies

Our systematic review, which is global in scope but draws on case studies from key irrigated regions in Asia, Africa, and Latin America, identifies a critical disconnect: the persistence of a performance gap is often rooted in the failure to integrate technical assessments with the socio-economic and institutional realities of water management. The rise of powerful new technologies now offers a pathway to bridge this gap. Advanced remote sensing platforms, such as the FAO's WaPOR database and high-resolution Sentinel-2 satellite imagery, provide unprecedented capabilities for monitoring agricultural water productivity and crop health (Tiruye et al., 2023). Simultaneously, the application of Artificial Intelligence (AI) is moving from a prospective tool to a demonstrated asset. For example, machine learning models are now being used to forecast crop water demand with high accuracy, enabling more efficient water allocation (Younes et al., 2024), while explainable AI (XAI) is being used to create transparent decision-support tools for irrigation managers (Chen et al., 2023; Mdemu et al., 2025).

Table 1. Summary of Key Performance Evaluation Frameworks.

Framework	Core Concept	Primary Objective	Key Contribution
Small & Svendsen (1990)	Nested Systems	To understand the interconnected purposes of irrigation, from water delivery to socio-economic impact.	Broadened the definition of performance beyond hydraulic efficiency to include agricultural and economic outcomes.
Murray-Rust & Snellen (1993)	Management-Oriented Diagnosis	To use performance data as a diagnostic tool for continuous improvement in management, operations, and maintenance.	Shifted the focus from a static audit of outputs to a dynamic process for improving management effectiveness.
Bos et al. (2005)	Systematic Staged Assessment	To provide a practical, purpose-driven process for designing and implementing actionable performance assessments.	Offered a structured, logical framework that links assessment purpose to methodology and ensures results are relevant to stakeholders.

1.5. Objectives and contribution of the review

Given that fragmented technical assessments are insufficient for building the resilient irrigation systems required for the future, the objective of the review is twofold. First, it is to systematically synthesize the evolution of performance assessment methodologies, charting the progression from traditional techniques to modern remote sensing and AI-driven approaches. Second, by highlighting the critical gap this synthesis reveals, namely, the persistent disconnect between technical metrics and socio-institutional realities, this review's primary contribution is to propose a novel, integrated socio-technical assessment framework. This framework offers an actionable blueprint that leverages modern technologies to guide the development of more productive, equitable, and climate-resilient canal irrigation systems.

2. Systematic review methodology

2.1. Review protocol

To ensure methodological transparency, rigor, and replicability, this systematic review was conducted in accordance with the PRISMA 2020 statement (Page et al., 2021). The adoption of this formal protocol directly addresses a critical weakness identified in previous versions of this work, which lacked a structured and defensible review methodology. The review protocol was designed a priori to answer four primary research questions:

1- How have the primary methodologies for assessing canal irrigation performance evolved?
2- What are the critical strengths, limitations, and areas of synergy among the core assessment approaches (direct measurement, remote sensing, and agro-hydrological modeling)?
3- What are the key non-technical (socio-economic, institutional, financial) factors identified in the literature as primary barriers to achieving high performance?
4- How can emerging technologies (e.g., advanced remote sensing, AI) and pressing future challenges (e.g., climate change) be integrated into a cohesive and forward-looking assessment framework?

2.2. Search strategy and information sources

A comprehensive literature search was conducted using a multi-tiered approach to ensure both rigor and broad coverage of relevant scientific literature and influential reports. The primary systematic search was performed in two major academic databases: Scopus and Web of Science (WOS). These databases were chosen due to their extensive indexing of high-quality, peer-reviewed scientific literature across multiple disciplines, providing a robust and replicable baseline. Our decision to focus the primary systematic search on these two databases and to systematically exclude general grey literature was made to ensure a consistent standard of peer-reviewed evidence.

This primary search was supplemented by a targeted manual search for two types of additional highly relevant sources: (1) Influential reports from key international organizations central to irrigation management, such as the International Commission on Irrigation and Drainage (ICID) and the Food and Agriculture Organization (FAO); and (2) A limited number of highly relevant peer-reviewed articles from other journals that were identified through the screening of reference lists of core review articles.

This hybrid strategy combines the systematic nature of database searching with the thoroughness of manual supplementation, ensuring our review is grounded in both a broad evidence base and seminal works in the field.

The search timeframe was set from 1990 to 2025, with the start date chosen to coincide with the publication of the influential Small & Svendsen (1990) framework, which marked a turning point in the conceptualization of irrigation performance. The search query was constructed using a combination of keywords and Boolean operators to capture the multidisciplinary nature of the topic. To ensure comprehensiveness and avoid omitting relevant studies, the search string was rigorously developed and included terms such as "benchmarking," "irrigation efficiency," "water productivity," "water delivery performance," "governance," and "machine learning." The core search string was:

("canal irrigation" OR "irrigation scheme" OR "irrigation system") AND ("performance assessment" OR "performance evaluation" OR "benchmarking" OR "irrigation efficiency" OR "water productivity" OR "water delivery performance") AND ("remote sensing" OR "agro-hydrological model" OR "socio-economic" OR "institutional" OR "governance" OR "climate change" OR "artificial intelligence" OR "machine learning")

2.3. Eligibility criteria and study selection

Studies retrieved from the database search were subjected to a rigorous three-stage screening process based on predefined inclusion and exclusion criteria, as illustrated in the PRISMA 2020 flow diagram (Figure 1).

Inclusion Criteria:

- Peer-reviewed journal articles, comprehensive review papers, and high-impact conference proceedings.
- Publication in the English language.

- The primary focus is on the performance of canal-fed surface irrigation systems.
- Studies that proposed, applied, or critically reviewed assessment frameworks, performance indicators, or specific methodologies (technical, socio-economic, institutional, or integrated).
- For the review, "high-impact conference proceedings" are precisely defined as: (1) proceedings from conferences sponsored by major international academic and professional societies in the fields of water resources and agricultural engineering (e.g., IAHS, ICID); and/or (2) proceedings that are fully indexed within the Scopus or Web of Science databases.

Exclusion Criteria:

Studies focused exclusively on on-farm irrigation technologies (e.g., drip, sprinkler) without a clear link to the performance of the canal delivery system.

- Studies focused exclusively on on-farm irrigation technologies (e.g., drip, sprinkler) without a clear link to the performance of the main canal delivery system.
- Studies concerning non-irrigation canals (e.g., for navigation, hydropower, or urban water supply).
- Grey literature (e.g., dissertations, theses, and non-peer-reviewed reports).

The selection process involved an initial screening of titles, followed by a review of abstracts, and concluded with a full-text assessment of potentially relevant articles. To minimize individual bias, all titles and abstracts were independently screened by two of the authors. Any discrepancies or uncertainties regarding the inclusion of a study were resolved through discussion and consensus with a third author.

The systematic search and screening process is rigorously summarized in the PRISMA 2020 flow diagram (Figure 1). The initial electronic search of Scopus and Web of Science databases yielded 2,130 records. An additional 47 records were identified through a manual search of reference lists from key review articles, resulting in 2,177 total records identified. After diligently removing 557 duplicate records, 1,620 unique records proceeded to title and abstract screening. This initial screening led to the exclusion of 640 records that were clearly outside the scope of the review (e.g., irrelevant topics, non-research articles). The full texts of the remaining 980 articles were then sought for retrieval and assessed for eligibility. Of these, 682 full-text articles could not be retrieved or were deemed unavailable. The remaining 298 full-text articles were then rigorously assessed against the predefined inclusion and exclusion criteria. This final eligibility assessment resulted in the exclusion of 200 articles. Ultimately, 98 studies were included in the qualitative synthesis of this present review. This transparent and systematic process ensures the replicability and robustness of our literature base upon which the review's conclusions are built.

2.4. Data extraction and synthesis

A structured data extraction template was developed and employed to systematically capture relevant information from each of the final included studies. The key variables extracted were categorized as follows: (i) Bibliometric Information (Authors, year, journal, study location); (ii) Study Objectives and Scope (Primary research question, scale of analysis); (iii) Performance Assessment Methodology (e.g., Direct Measurement techniques, Remote Sensing platforms/indices, Agro-hydrological models, Socio-economic survey methods); (iv) Key Performance Indicators (KPIs) (Specific metrics used, such as efficiency, equity, adequacy, reliability); (v) Key Findings and Conclusions (Main outcomes and limitations identified by the authors); and (vi) Limitations and Future Research Directions (Author-identified limitations of their study and suggestions for future work). To ensure reliability, one author conducted the primary data extraction, and a second author independently verified a random 25% sample of the extracted data for accuracy and completeness.

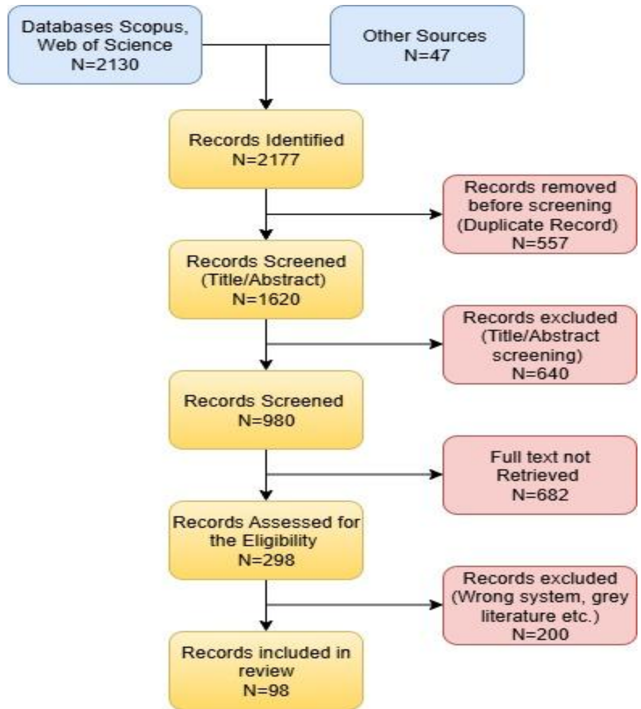

Figure 1. PRISMA 2020 flow diagram for the systematic review.

Given the heterogeneity of the methodologies, scales, and contexts of the included studies, a quantitative meta-analysis was not feasible. Therefore, we applied a qualitative, narrative synthesis approach. This analytical framework involved identifying, grouping, and summarizing findings across studies to develop a coherent narrative. This approach was chosen because it is ideally suited for integrating evidence from diverse study types to identify recurring themes, trace the evolution of methodologies, and identify critical knowledge gaps—all of which were central to our objective of developing a new conceptual framework.

3. The methodological triad in performance assessment: a critical synthesis

The practice of canal performance assessment is built upon a triad of core methodologies: direct field measurement, remote sensing (RS), and agro-hydrological modeling. These approaches are not mutually exclusive competitors; rather, they form a complementary toolkit, each with distinct strengths and limitations. The evolution of the field can be understood through the progression and, more importantly, the integration of these three pillars. Our systematic review found that approximately 55% of the included studies primarily relied on RS, 25% on modeling, 10% on direct measurement, and 15% employed integrated/hybrid approaches. A key operational approach for combining these methods in practice, particularly in research settings, involves data assimilation, where satellite-derived observations (e.g., ETa, soil moisture, LAI) are used to calibrate and update agro-hydrological models, improving their accuracy and predictive power (Han et al., 2019; Kumar et al., 2019). Comparative Analysis of Core Performance Assessment Methodologies is summarized in Table 2.

3.1. Foundational approaches: the role and limitations of Direct Measurement

Direct field measurement is the bedrock of performance assessment, providing the essential "ground truth" against which all other methods are ultimately validated. This approach involves the physical measurement of key variables within the canal command area, such as canal discharges using flow measurement structures, crop yield samples from designated plots, and socio-economic data through farmer surveys. This high-fidelity, localized data is indispensable for calculating the classical performance indicators that defined the field for decades, including hydraulic metrics like conveyance and application efficiency, and service delivery metrics like adequacy, equity, and dependability (Bantero et al., 2011). Seminal studies, such as that by Molden and Gates (1990), utilized field data to establish quantitative benchmarks for these indicators, creating a standardized basis for comparison. Subsequent work by Bos et al. (1991) in Argentina assessed distribution accuracy, and Burt & Styles (1998) compared multiple systems using a broad set of internal and external indicators. Later, Molden et al. (1998) introduced economic indicators for strategic cross-system comparisons.

Throughout the 2000s, researchers expanded on this foundation. Studies combined field data with economic metrics in Pakistan (Tahir & Habib, 2000), used soil-water balance techniques in Spain (Isidoro et al., 2004), and applied the Penman-Monteith equation to assess tertiary-level performance in Mali and Turkey (Korkmaz et al., 2009; Vandersypen et al., 2006). These field-based methods provide high-fidelity, localized data indispensable for calculating classical performance indicators (Mishra et al., 2023; Nigam et al., 2023a; Somda et al., 2020).

Despite its precision, the direct measurement approach is constrained by significant practical limitations. It is exceptionally resource-intensive, requiring substantial investment in time, labor, and equipment, which often makes it prohibitively expensive for routine or large-scale applications. Consequently, its use is typically restricted to smaller, targeted case studies or to the higher hierarchical levels of a system, such as the main and secondary canals, where measurement points are fewer (Bastiaanssen & Bos, 1999; Jiang et al., 2015). This approach fundamentally struggles to capture the vast spatial heterogeneity of water use and crop production across thousands of individual farm plots within a large command area and is ill-suited for the kind of continuous, real-time monitoring required for dynamic operational management (Gowing, 1998).

The field is actively evolving to address these constraints. To reduce costs and enhance sustainability, particularly in low-income countries and data-scarce regions, reviewed studies demonstrate innovative strategies such as the development of low-cost, open-source flow sensors (Obaideen et al., 2022), the implementation of farmer-led participatory monitoring initiatives (Namara et al., 2010), and the use of mobile applications for simplified data collection (Cerjak et al., 2025). In the context of climate change and the growing need for real-time water management, traditional field-based data collection is increasingly integrated into dynamic monitoring frameworks. Examples from the reviewed literature include Supervisory Control and Data Acquisition (SCADA) systems that feed real-time sensor data into operational models for dynamic gate control and water ordering (Abhilash et al., 2022), and smartphone-based applications allowing water users to report water availability and demand, integrating into management dashboards (Cerjak et al., 2025). These advancements demonstrate how digitized field data can support responsive decision-making. Consequently, the consensus is that direct measurements are most practical at higher hierarchical levels of an irrigation system and remain essential for validating other, more scalable assessment methods.

3.2. The spatial revolution: advances in Remote Sensing for command area monitoring

The advent of satellite-based remote sensing (RS) revolutionized performance assessment by overcoming the scale limitations of direct measurement. RS provides a synoptic, spatially continuous view of the entire command area, enabling objective and repeatable monitoring (Bastiaanssen & Bos, 1999). The technological evolution in this domain has been rapid. Early applications relied on vegetation indices like the Normalized Difference Vegetation Index (NDVI), derived from optical sensors, to map crop types, assess vegetation health, and monitor the extent of irrigated areas (Amarasinghe et al., 2021; Nikam et al., 2020). A major leap forward came with the widespread application of thermal infrared data to drive Surface Energy Balance (SEB) models, such as SEBAL (Surface Energy Balance Algorithm for Land) (Derardja et al., 2024). These models estimate actual evapotranspiration (ETa), the total water consumed by evaporation and plant transpiration, which serves as a direct, spatially explicit measure of water use and is a critical input for calculating water productivity (Mekonnen et al., 2024; Waqas et al., 2021).

There are many studies observed during the timeframe considered. The performance carried out in South Asia with analyzing water productivity using SEBAL Eta calculation (Bastiaanssen et al., 2003; Sakthivadivel et al., 1999). The studies carried out with the different input data, like MODIS (El-Agha et al., 2011), Landsat and SPOT (Kharrou et al., 2013), LISS-III (Kumar et al., 2014), and Sentinel-2 (Mekonnen et al., 2024), for performance analysis.

The current state-of-the-art is characterized by increasingly powerful and accessible platforms that are transforming assessment capabilities:

- **High-resolution optical and thermal data:** The Copernicus program's Sentinel-2 constellation provides freely available optical imagery at a high spatial resolution (10 m) and frequent revisit time (approx. 5 days). This enables monitoring at the individual field scale, allowing for the derivation of crop-specific parameters like the basal crop coefficient (Kcb) and the precise estimation of crop water requirements across diverse and fragmented agricultural landscapes (El Hachimi et al., 2022; Er-Rami et al., 2021; Maselli et al., 2020). Future missions like the Copernicus Land Surface Temperature Monitoring (LSTM) mission promise to deliver high-resolution thermal data, which will further enhance the accuracy of ET estimation and crop stress detection (Derardja et al., 2024; Mekonnen et al., 2024).
- **Integrated water accounting platforms:** The Food and Agriculture Organization's (FAO) WaPOR portal (https://data.apps.fao.org/wapor/) represents a paradigm shift in data accessibility. It provides open-access, continental-scale datasets on key performance variables, including ETa, biomass production, and water productivity, derived from satellite data. This democratizes performance assessment, empowering local water managers, researchers, and even farmer associations to conduct consistent and standardized benchmarking of their systems without requiring extensive technical expertise in RS data processing (Blatchford et al., 2020). Case studies using WaPOR have demonstrated its utility in assessing indicators like adequacy, equity, and uniformity across large schemes (Amsalu & Mulu, 2025; Chukalla et al., 2022; Tiruye et al., 2023). However, our review indicates that while these products hold great potential and are widely used in research, their effective day-to-day application by Water User Associations (WUAs) or local irrigation managers remains limited in many regions. Key reported barriers to knowledge transfer from research to practice include a lack of technical capacity at the local level, insufficient integration with existing decision-support systems, and inadequate training programs (Blatchford et al., 2020; Khaspuria et al., 2024).

Despite these advances, challenges remain. Optical and thermal sensors are limited by cloud cover, which can create significant data gaps, particularly in monsoon climates (Li et al., 2025; Uday et al., 2025). Our review assessed the impact of these limitations on reliability, identifying alternative approaches in the literature such as the use of Synthetic Aperture Radar (SAR) data (e.g., from Sentinel-1), which can penetrate clouds and provide all-weather monitoring for soil moisture and flood mapping (Mkhwenkwana et al., 2025). Furthermore, data fusion techniques, combining optical with SAR or other sensor types, and spatio-temporal gap-filling algorithms are presented as promising methods for generating more complete and reliable datasets (Mao et al., 2023), thus mitigating the impact of cloud limitations. All RS-derived products require robust atmospheric correction and, crucially, periodic ground-truthing with field measurements to ensure their accuracy and local validity. Our analysis suggests that while ground-truthing is acknowledged as important, the extent and scale of field data used to validate RS outputs vary. While many research-oriented studies emphasized rigorous validation against comprehensive field data (e.g., flux towers, crop coefficient) (Alataway et al., 2019; Xue et al., 2021), a significant number of practical applications, especially those relying on publicly available, pre-processed products like WaPOR, often used less intensive or assumed validation (Blatchford et al., 2020). Encouragingly, rather than focusing on single indicators, our review identified integrative frameworks that combine multiple RS-derived indicators (e.g., crop classification, evapotranspiration, biomass production, and equity in water distribution) into coherent multi-criteria performance assessment systems. Examples include multi-indicator dashboards and spatially explicit water accounting models that are fed entirely by RS data (Chukalla et al., 2022; Han et al., 2019; Zafar et al., 2021).

3.3. The predictive frontier: Agro-hydrological modeling for scenario analysis

The third pillar of the methodological triad is agro-hydrological modeling. Models such as SWAP, SWAT, CROPWAT, AquaCrop, Hydrus, etc, are powerful analytical tools that simulate the complex, dynamic interactions within the soil-water-atmosphere-plant continuum. While RS excels at observing the current state of a system, the unique strength of modeling lies in its predictive capability. Models allow analysts to move beyond assessing past performance to exploring a range of "what-if" scenarios, making them indispensable for planning and strategic management (Uniyal & Dietrich, 2021).

Key applications in performance assessment include estimating spatially distributed crop yield, crop water requirements, and analyzing the components of the water balance (e.g., quantifying non-beneficial losses like deep percolation and runoff) (Woznicki et al. 2015). Critically, evaluating the potential impacts of future climate change on water availability, demand, and impact on performance under water stress conditions (Basukala et al., 2024; Li & Ren, 2019; Liu et al., 2018). These models can simulate how a system might perform under projected future climate scenarios (e.g., from CMIP6 models), thereby testing the efficacy of various adaptation strategies before they are implemented (Rudraswamy & Umamahesh, 2024). Our review identified several studies that demonstrated the application of these approaches in low-income countries and data-scarce regions by utilizing globally available datasets for soil and weather and by incorporating participatory methods to estimate key management parameters, thus making robust modeling feasible under such constrained conditions (Basukala et al., 2024; Kaini et al., 2024; Mishra et al., 2023).

The most powerful modern application of these models lies in their synergy with remote sensing. The assimilation of satellite-derived data, such as ETa or Leaf Area Index (LAI), to calibrate and validate model parameters has been shown to dramatically improve their spatial accuracy and reduce predictive uncertainty (Han et al., 2019; Niu et al., 2018; Van Dam et al., 2006). This integration combines the observational power of RS with the process-based understanding and predictive capacity of models. However, the use of agro-hydrological models is not without its challenges. They are often data-intensive, requiring extensive inputs on soil, climate, and crop parameters for proper setup and calibration (Uniyal et al. 2019). The process of parameterization can be complex, and all models contain inherent uncertainties that must be carefully quantified and communicated to end-users.

4. Discussion: towards an integrated, forward-looking assessment framework

The synthesis of the methodological triad reveals a clear trajectory towards more spatially comprehensive and predictive assessments. However, it also exposes a fundamental limitation: a purely technical evaluation, no matter how advanced, is insufficient to diagnose and solve the persistent underperformance of many canal systems. The most sophisticated remote sensing algorithm can quantify inequity in water distribution, but it cannot explain *why* that inequity exists. The answer often lies not in the physics of water flow, but in the complex interplay of institutions, economics, and human behavior. A truly effective assessment framework must therefore bridge this technical-social divide and be forward-looking, accounting for the profound challenges of climate change and the opportunities presented by emerging technologies like AI.

4.1. Bridging the technical-social divide: incorporating Institutional and Socio-economic dimensions

A common metaphor in development is that of "hardware" and "software." In canal irrigation, the physical infrastructure—dams, canals, and gates is the hardware. The institutions, governance structures, policies, and social norms that dictate how that hardware is used constitute the software (CWC, 2002). Decades of experience have shown that even the most well-designed hardware will fail if the software is dysfunctional. Technical performance indicators, such as low delivery efficiency or poor equity, are often symptoms of deeper, systemic failures in this institutional software (Amarasinghe et al., 2021).

A systematic review of the literature reveals a consistent set of non-technical barriers that plague canal systems globally, which can be categorized as follows:

- **Financial barriers:** The most frequently cited barrier is a chronic lack of funding for operation and maintenance (O&M). This stems from insufficient government allocations, coupled with a poor system of cost recovery from users. Water User Associations (WUAs) are often unable to collect adequate water fees, rendering them financially unviable and incapable of performing routine maintenance, leading to a downward spiral of infrastructure decay and declining service quality (Amarasinghe et al., 2021; Nigam et al., 2023b; Zafar et al., 2021).
- **Legal and Institutional barriers:** Performance is often hampered by an inadequate or ambiguous legal framework governing water rights, the responsibilities of WUAs, and the process of irrigation management transfer from the state to users. Without clear and enforceable rules for water distribution and conflict resolution, political interference and capture of resources by powerful elites can become rampant, undermining any attempt at equitable management (Nigam et al., 2023b).
- **Capacity and Social Barriers:** The effectiveness of WUAs and irrigation agencies is frequently limited by a lack of technical and managerial capacity. Insufficient training in financial management, water scheduling, and conflict resolution weakens these institutions from within (Nigam et al., 2023b). Furthermore, social dynamics, including pre-existing inequalities, lack of trust between farmers and officials, and internal disputes over water allocation, can paralyze collective action and render even well-structured WUAs ineffective (Mwadzingeni et al., 2022).

Therefore, a modern performance assessment must adopt a mixed-methods approach that integrates quantitative technical data with qualitative institutional and socio-economic analysis (Mohammedshum et al., 2023). This creates a multi-layered diagnostic process. For example, remote sensing might first identify a "hotspot" of low water productivity in a tail-end distributary. Agro-hydrological modeling could then test whether this is due to insufficient water supply or other agronomic factors. Finally, on-the-ground institutional analysis, through farmer surveys and stakeholder workshops, would diagnose the root cause: is it a result of a broken control gate (a technical problem), illegal upstream water abstraction (a governance problem), or the collapse of the local WUA's fee collection system (a financial and social problem)? Only by integrating these perspectives can the correct problem be diagnosed and the appropriate intervention be designed. This multi-layered diagnostic process is central to the proposed integrated socio-technical assessment framework (Figure 2). As depicted, the framework integrates insights from The Methodological Triad with Institutional & Socio-Economic Analysis.

Table 2. Comparative analysis of core performance assessment methodologies.

Attribute	Direct Measurement	Remote Sensing	Agro-hydrological modeling	Integrated approaches (Hybrid)
Key outputs	Point/local measurements of flow, yield, water quality; Survey data.	Spatially continuous maps of crop type, vegetation health (NDVI), actual water use (ETa), and water productivity.	Spatially distributed estimates of water balance components, crop water demand, yield, and Future scenario predictions.	Holistic performance dashboards combining ground truth, spatial patterns, and future projections; Actionable insights for dynamic management.
Spatial scale	Point to field/tertiary canal level.	Field to command area, basin, and continental scale.	Field to command area and basin scale.	Field to basin scale, leveraging strengths of all components.
Temporal scale	Intermittent (campaign-based) to continuous (at select points).	Periodic (satellite revisit time, e.g., 5-16 days); subject to cloud cover.	Continuous simulation (e.g., daily time-step) for historical and future periods.	Near real-time to continuous historical and future analysis, filling data gaps.
Data requirements	Low initial data, but high for ongoing measurement (field crews, equipment).	Satellite imagery, meteorological data, and ground-truthing data for validation.	Extensive input data: climate, soil properties, crop parameters, management practices, and canal network data.	Integrates all data types; benefits from data sharing and interoperability.
Cost/resource intensity	High operational cost (labor, travel, equipment).	Low data acquisition cost (for public data), moderate-to-high expertise required for processing.	High initial setup cost (data collection, calibration), low cost for subsequent simulations.	Moderate initial investment (platforms, training) but highest long-term value for actionable insights.
Key strengths	Provides "ground truth" data; High accuracy at the point of measurement; Can measure variables not visible from space (e.g., groundwater levels, institutional factors).	Excellent spatial coverage; Objective and repeatable; Can monitor inaccessible areas; Enables historical analysis and benchmarking.	Predictive capability for scenario analysis (e.g., climate change, policy changes); Simulates unseen processes (e.g., deep percolation).	Overcomes individual limitations; provides holistic, multi-dimensional, and actionable insights; best for dynamic, adaptive management.
Critical limitations	Poor spatial representation; Labor- and time-intensive; Impractical for large-scale, continuous monitoring.	Limited by cloud cover; Indirect measurement requires validation; Can be less accurate for certain variables; Temporal resolution can be a constraint.	High data dependency; Model structure and parameter uncertainty; Requires significant expertise for calibration and validation.	Requires significant technical capacity and interdisciplinary expertise for setup and maintenance; Challenges in integrating diverse data formats.
Uncertainty considerations	Low inherent uncertainty at the specific measurement point, but high when extrapolating spatially. Reliability is heavily dependent on sampling design.	Moderate. Main sources: atmospheric correction, sensor calibration, model parameterization.	The highest potential uncertainty due to input data, model structure, and parameterization.	Aims to reduce overall uncertainty by cross-validating and complementing data sources, though it introduces integration complexities.
Applicability in Low-resource contexts	Feasible with targeted, optimized sampling, low-cost sensors, and participatory monitoring.	High potential with free datasets (Sentinel, WaPOR), but requires capacity building for data processing and interpretation.	Feasible with global datasets and participatory parameterization, but high initial setup expertise is required.	Offers the most promising long-term value for money after initial capacity building and system setup.

This framework is operationalized through a sequential, explanatory mixed-methods design. Specific tools include geospatial analysis platforms (e.g., QGIS, Google Earth Engine) for RS data, simulation models (e.g., SWAT, AquaCrop) for biophysical analysis (Han et al., 2019; Zafar et al., 2021), and structured qualitative methods like semi-structured interviews, focus group discussions, and Participatory Rural Appraisal (PRA) for socio-institutional insights (Makin, 2023). The integration of quantitative and qualitative data can occur through "joint displays," where, for example, a map of RS-derived water inequity is overlaid with key themes from farmer interviews, creating a unified diagnostic narrative (Azari & Rizi, 2021; Zafar et al., 2021). This framework, while robust, emphasizes context-sensitivity; its application requires adaptation to local socio-economic, institutional, and climatic conditions to avoid being overly generic.

4.2. Assessing for resilience: performance evaluation in the context of Climate change

Traditional performance assessment is largely a retrospective exercise, evaluating how efficiently a system operated in the past. In an era of accelerating climate change, this is no longer sufficient. Assessment must become prospective, evaluating a system's capacity to perform under future conditions of increased uncertainty and stress. The goalposts are shifting from optimizing for historical efficiency to designing for future resilience (Mwadzingeni et al., 2022).

Climate change is projected to impact canal systems in multiple ways: altering the volume and timing of water availability due to changes in precipitation and snowmelt patterns; increasing crop water demand due to higher temperatures and longer growing seasons; and raising the risk of damage to physical infrastructure from more frequent and intense extreme weather events, such as floods and droughts (Mdemu et al., 2025).

Consequently, future performance assessments must incorporate new indicators designed to measure resilience and adaptive capacity:

- **System robustness:** This metric assesses the ability of the physical infrastructure and its operational rules to maintain function across a wider range of hydrological variability than historically experienced. Measurable aspects include the frequency and duration of water delivery failures under stress scenarios, the capacity of infrastructure to withstand extreme events without catastrophic breakdown, and the ability of a system to recover its pre-stress performance within a defined timeframe (Kazem Shahverdi, 2025; Krishan et al., 2018).
- **Adaptive capacity:** This evaluates the ability of the system's human components, farmers, WUAs, and government agencies to learn, innovate, and adjust management practices in response to evolving climatic signals and socio-economic conditions (Mwadzingeni et al., 2022). Metrics could involve the speed of policy adjustment, adoption rates of climate-smart agriculture technologies, diversification of water sources, or the institutional flexibility to reallocate water rights during scarcity (Gamage et al., 2024; Wakweya, 2023).

Agro-hydrological models are the primary tools for this forward-looking assessment. By driving these models with downscaled climate projections from General Circulation Models (e.g., CMIP5 or 6), analysts can simulate future system performance and test the effectiveness of various adaptation strategies, such as changing cropping patterns, investing in water storage, or modifying operational rules (Basukala et al., 2024; Kaini et al., 2024; Liu et al., 2018). The inherent uncertainties in climate projections, model parameters, and input data are critical and must be systematically addressed. This is proposed through rigorous uncertainty quantification techniques such as sensitivity analysis, probabilistic scenario analysis, and ensemble modeling, providing a range of possible outcomes rather than single predictions (FAO, 2013; Hussain et al., 2025). Incorporating these uncertainties into decision-making involves presenting probabilities of different outcomes to stakeholders, enabling risk-informed planning and the identification of robust solutions that perform well across a spectrum of plausible futures.

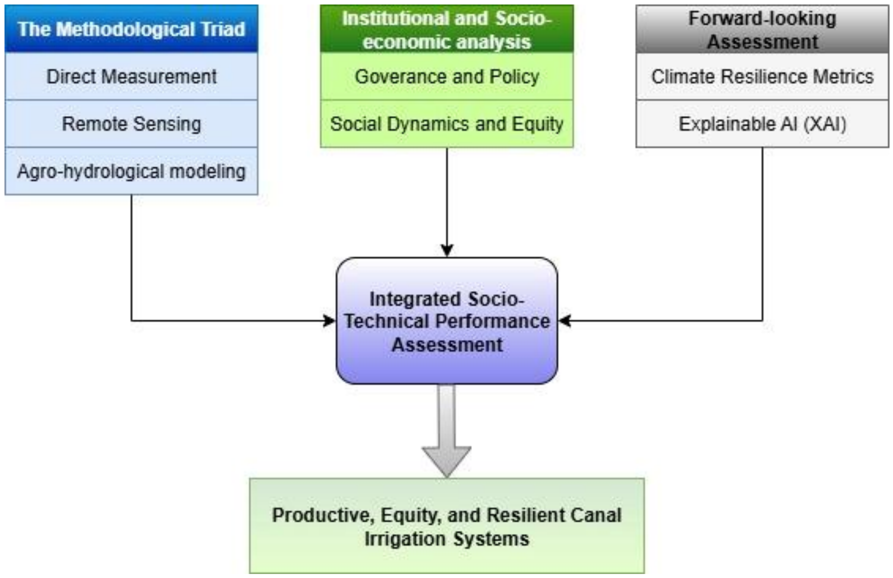

Figure 2. The proposed Integrated Socio-technical assessment framework for Canal irrigation systems.

4.3. The next technological wave: the role of AI and Machine Learning

Artificial Intelligence and Machine Learning (AI/ML) represent the next frontier in the evolution of canal system management, offering the potential to move from passive performance monitoring to active, intelligent, and optimized operations. While still an emerging field for large-scale canal networks, applications at the field and sub-system level demonstrate significant promise.

Key applications of AI/ML relevant to canal performance include:

- **Predictive analytics:** ML models, such as Artificial Neural Networks (ANNs), Random Forests (RF), and Support Vector Machines (SVMs), have proven highly effective at forecasting key variables like irrigation water demand, canal flow rates, and soil moisture, often with greater accuracy and computational efficiency than traditional process-based models (Belarbi & El Younoussi, 2025; Younes et al., 2024).
- **Optimization of operations:** Algorithms can be used to optimize water allocation and delivery schedules across an entire canal network. By processing real-time data on supply, demand, and system constraints, these tools can recommend gate operations that maximize objectives like overall water productivity or equity in distribution (Shahverdi, 2025).
- **Data fusion for decision support:** The true power of AI lies in its ability to integrate and learn from diverse, large-scale datasets. Future decision support systems will fuse real-time data streams from multiple sources—remote sensing platforms, in-field IoT sensors, weather forecasts, and market prices to provide comprehensive, data-driven recommendations to both canal managers and farmers (Farig et al., 2025).

The integration of these technologies, however, has profound governance implications. An AI system designed solely to optimize for water productivity might inadvertently recommend water allocation strategies that are technically efficient but socially inequitable, for example, by prioritizing the high-value cash crops of already wealthy farmers over the subsistence food crops of poorer, tail-end users. This raises a critical future challenge: designing "socio-technically aware" AI systems that can optimize for multiple, sometimes competing, objectives, including equity, environmental sustainability, and social justice.

Safeguarding social equity and inclusion of vulnerable groups within this integrated framework requires several mechanisms: (1) establishing explicit ethical guidelines and regulatory frameworks for AI in water management; (2) implementing participatory design processes for AI tools that actively involve diverse stakeholder groups, especially vulnerable farmers, to ensure their needs and values are reflected; (3) integrating equity-focused metrics (e.g., water access disparity, distribution of benefits) directly into AI's objective functions and monitoring frameworks; and (4) ensuring transparent and explainable AI (XAI) outputs to build trust and allow for accountability (Maggo, 2025; Zhu et al., 2022).

The performance assessment of the future will therefore need to evaluate not only the performance of the canal system itself but also the fairness, transparency, and accountability of the algorithms that help to govern it. Key research frontiers include the development of large, high-quality training datasets for canal systems, improving the transferability of models across different regions, and advancing the field of explainable AI (XAI) to build trust and facilitate adoption among stakeholders (Zhu et al., 2022).

The overall adaptability and transferability of this proposed framework (Figure 2) across diverse settings (socio-economic, institutional, climatic) is ensured by its multi-faceted and adaptive nature. It is not a rigid, one-size-fits-all solution but a diagnostic approach. Its context-sensitivity across the literature (Section 4.1), is that technical sophistication alone is insufficient. The persistent gap between potential and actual performance in many of the world's canal systems is primarily a function of deep-seated financial, institutional, and social barriers. Effective and sustainable canal management, therefore, demands an integrated assessment framework that synthesizes robust technical methodologies with a nuanced understanding of socio-institutional dynamics, prepares for the future by incorporating climate resilience, and harnesses the potential of emerging AI technologies. This integrated framework directly emerges from the synthesis of findings across Sections 3 and 4, which collectively reveal the necessity of combining disparate technical and social methods for holistic problem diagnosis and future-oriented solutions.

5.2. Implications for policy and practice

The findings of the review offer several actionable recommendations for those tasked is inherent in the qualitative data collection component (interviews, PRA), which directly assesses local institutional and social conditions, and in the flexible application of remote sensing and modeling tools, which can be calibrated to local agro-climatic specificities. This allows the framework to identify universally relevant challenges while still tailoring interventions to unique local contexts.

5. Conclusion

5.1. Recapitulation of findings

This systematic review has systematically charted the evolution of performance assessment in canal irrigation systems, tracing its path from a narrow focus on hydraulic efficiency to the complex, multidisciplinary challenge it represents today. The analysis confirms a clear progression in technical methodologies, from labor-intensive direct measurements to the vast spatial reach of remote sensing and the predictive power of agro-hydrological modeling. The state-of-the-art lies not in choosing one method, but in their synergistic integration, as evidenced by the increasing adoption of hybrid approaches discussed in Section 3. However, the central argument of the review, unequivocally supported by the consistent non-technical barriers identified with managing, funding, and regulating canal irrigation systems, strongly supported by the evidence reviewed in Sections 3 and 4:

- **Invest in "Software" alongside "Hardware":** Policymakers and funding agencies should shift from a model that prioritizes investment in physical infrastructure ("hardware") to one that gives equal weight to "software." This means co-investing in strengthening Water User Associations, developing transparent and enforceable water allocation policies, and building the technical and managerial capacity of both farmers and agency staff. This recommendation is a direct consequence of the widespread evidence of non-technical barriers detailed in Section 4.1.
- **Adopt a tiered, diagnostic assessment approach:** Irrigation managers should adopt a multi-scale assessment strategy. Broad-scale, routine monitoring can be conducted cost-effectively using open-access remote sensing

tools like FAO's WaPOR to identify system-wide trends and pinpoint "hotspots" of underperformance. These findings should then trigger more intensive, targeted diagnostics at the local level, using a combination of direct measurement and socio-economic analysis to understand the specific root causes of the identified problems. This approach directly operationalizes the mixed-methods integration described in Section 4.1.

- **Mainstream Climate resilience into planning:** Performance assessment must become a forward-looking exercise. All new irrigation projects and modernization plans should be explicitly evaluated for their resilience to future climate change impacts, using scenario-based modeling to test the robustness of infrastructure and the adaptability of management plans. This is a crucial implication drawn from the discussion on climate change impacts and resilience assessment in Section 4.2.

5.3. A structured agenda for future research

This study identifies several critical research gaps and proposes a structured agenda to guide future scientific inquiry in the field, as summarized in Table 3. The goal is to move beyond incremental improvements in individual methods and toward a more holistic and impactful science of performance assessment.

Table 3. Identified research gaps and proposed future directions.

Thematic area	Identified gap	Key research questions	Potential methodologies
Socio-Technical Integration	Lack of standardized methods for integrating qualitative institutional data with quantitative technical metrics.	How can institutional performance (e.g., governance quality, conflict resolution effectiveness) be quantified and causally linked to technical outcomes like water productivity and equity? How can participatory assessment methods be rigorously combined with remote sensing data?	Mixed-methods research designs; Development of composite socio-technical performance indices; Bayesian Belief Networks to model interactions between social and physical variables.
Climate Resilience Assessment	Resilience and adaptive capacity are well-understood concepts but are rarely quantified as part of routine performance assessments.	What are robust, measurable, and transferable indicators of adaptive capacity for canal irrigation systems? How does institutional flexibility influence a system's ability to cope with climate-induced water shocks?	Dynamic vulnerability mapping; Agent-based modeling to simulate farmer adaptation behavior under climate stress; Time-series analysis of system performance in response to historical climate extremes.
Advanced Remote Sensing	Need for robust validation of new high-resolution ET products across diverse crop types and agro-ecological zones.	How can data fusion techniques synergistically combine optical, thermal, and radar (e.g., SAR) data to provide all-weather, high-resolution estimates of evapotranspiration and soil moisture?	Development of multi-sensor data fusion algorithms; Establishment of long-term flux tower validation sites in under-represented regions; Use of Unmanned Aerial Vehicles (UAVs) for ultra-high-resolution ground-truthing.
AI and Machine Learning	Most AI/ML research is focused on the field scale; applications for optimizing operations across complex, multi-user canal networks are limited.	How can explainable AI (XAI) be used to develop transparent and trusted decision support systems for canal operators? How can reinforcement learning be applied to train models for dynamic, real-time canal gate control? What are the equity implications of AI-driven water allocation, and how can fairness be built into optimization algorithms?	Development of hybrid models combining ML with hydraulic simulation; Application of XAI techniques (e.g., SHAP, LIME) to irrigation models; multi-objective optimization algorithms that incorporate equity and environmental constraints.

This structured agenda, presented in Table 3, clearly articulates a path forward by translating identified gaps into specific, actionable research questions and proposing potential methodologies. This provides a focused roadmap for future scientific inquiry, aiming to bridge the critical gaps identified in the review through targeted methodological advancements.

5.4 Limitations of the review

The current review offers a comprehensive synthesis; it is important to acknowledge certain limitations that bound its scope and findings. Our systematic search was restricted to specific English-language databases, which may introduce a language bias and exclude relevant literature published in other languages or less accessible grey literature. Furthermore, the qualitative nature of this synthesis, while robust for identifying thematic trends, did not include a quantitative meta-analysis. This means we focused on synthesizing concepts and methodological approaches rather than statistically comparing quantitative performance indicators across studies. Finally, while we discuss the generalizability of the proposed framework, it is ultimately a conceptual model whose practical implementation will require careful adaptation to the unique socio-economic, institutional, and climatic contexts of diverse irrigation systems, as highlighted in Section 4.

Author Contributions:

Mohansing Rajaput: Collection and segregation of literature, writing, and editing. **Abhilash Ramadasa:** Segregation of literature, Writing, reviewing, and editing. **Basavanand M. Dodamani:** Review, editing, and supervision.

Conflicts of interest:

The authors of this article declared no conflict of interest regarding the authorship or publication of this article.

Data availability statement:

Data sharing does not apply to this article, as it is a review paper and no new datasets were generated or analyzed. All studies and reports analyzed during this review are publicly available and have been cited in the text and listed in the References section.

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